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ABBREVIATIONS

BCS Business and Consumer Surveys

BEIR Breakeven Inflation Rate

BS Balance Statistics

CES Consumer Expectations Survey

CP Carlson Parkin

EC European Commission

EU European Union

FED Federal Reserve System

HICP Harmonized Index of Consumer Prices

GFC Global Financial Crisis

RMSE Root Mean Squared Error

YoY Year over Year

TABLE OF CONTENTS

INTRODUCTION.....	16
1. THEORETICAL BACKGROUND AND LITERATURE REVIEW ON INFLATION EXPECTATIONS.....	22
1.1. The Role of Expectations in Economic Thought.....	22
1.2. Inflation Expectations Measurement and Effects.....	26
1.2.1. Importance of Inflation Expectations.....	26
1.2.2. Measuring Different Types of Inflation Expectations.....	27
1.2.3. Econometric Approach to Measuring Expectations.....	31
1.2.4. Debate on the Effects of Inflation Expectations.....	32
1.3. Recent Findings in Research of Inflation Expectations.....	34
1.3.1. Measurement Innovation.....	35
1.3.2. Randomized Controlled Trials.....	36
1.3.3. Heterogeneity and Formation of Expectations.....	38
1.3.4. Expectations of Firms.....	41
1.3.5. Macroeconomic Modelling Advances.....	42
1.3.6. Concluding Remarks.....	43
2. THE CARLSON-PARKIN QUANTIFICATION METHOD: ASSUMPTIONS AND EXTENSIONS.....	45
2.1. Consumer Survey Data.....	45
2.2. Carlson-Parkin Method.....	46
2.3. Quantification of Qualitative Expectations.....	50
2.4. Scaling Parameter.....	53
3. CONSUMER INFLATION EXPECTATIONS QUANTIFICATION AND ACCURACY IN THE BALTIC COUNTRIES.....	56
3.1. Data Overview.....	56
3.2. Quantification of Inflation Expectations.....	66
3.3. Predictive Power of Quantified Consumer Inflation Expectations.....	78
3.4. Concluding Remarks.....	83

4. COMPARATIVE EVALUATION OF CARLSON-PARKIN SPECIFICATIONS WITHIN A PANEL VAR FRAMEWORK FOR EU CONSUMER INFLATION EXPECTATIONS	85
4.1. Method.....	85
4.2. Results	88
4.2.1. Carlson-Parkin Method and Panel Vector Autoregression.....	93
4.2.2. Forecast Error Variance Decomposition	96
4.2.3. Vector Autoregression on Individual Countries.....	97
4.2.4. Concluding Remarks	99
5. SOCIO-DEMOGRAPHIC HETEROGENEITY: SUBGROUP-BASED QUANTIFICATION AND ACCURACY IMPROVEMENT	101
5.1. Lithuanian Household Data	101
5.2. Carlson-Parkin Method on Subcategory Data	116
5.3. Results of Subgroup Data Quantification	117
5.4. Concluding Remarks	120
CONCLUSIONS	122
BIBLIOGRAPHY	127
ANNEX A	135
ANNEX B	147
SANTRAUKA	191
ACKNOWLEDGEMENTS	228
PRESENTATIONS AT CONFERENCES	229
LIST OF PUBLICATIONS.....	230
TRUMPOS ŽINIOS APIE DISERTANTĄ	231

LIST OF TABLES

Table 1. Literature on CP method employing non-normal distributions.	49
Table 2. Descriptive statistics of YoY inflation.	61
Table 3. Descriptive statistics of Balance statistics of consumer inflation expectations.	62
Table 4. Cross correlation between YoY inflation and balance statistics....	65
Table 5. Augmented Dickey-Fuller and Phillips-Perron test results.	68
Table 6. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using actual YoY inflation (π_t) as a scaling parameter.	72
Table 7. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using 1 period lagged actual YoY inflation ((π_{t-1})) as a scaling parameter.	73
Table 8. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using perceived YoY inflation ($(\pi_{t,p})$) as a scaling parameter. Actual inflation ((π_{t-12})) has been used as a scaling parameter for quantifying perceived inflation.	74
Table 9. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using perceived YoY inflation ($(\pi_{t,p})$) as a scaling parameter. Average of inflation from the beginning of the sample period to the time when the survey was conducted has been used as a scaling parameter for quantifying perceived inflation.	75
Table 10. Regression results testing predictive power of quantified consumer inflation expectations. Significant at the 0.10 level (*); significant at the 0.05 level (**); significant at the 0.01 level (***)	80
Table 11. Regression results testing predictive power of balance statistics of consumer responses on inflation expectations. Significant at the 0.10 level (*); significant at the 0.05 level (**); significant at the 0.01 level (***)	81
Table 12. Summary of VAR impulse response functions of select macroeconomic variables to a positive shock of inflation expectations (BS_YOY) for individual countries.	98
Table 13. Balance statistics means of Lithuanian households by subcategory - age. Sample period 2011.01-2025.05.....	103
Table 14. Balance statistics means of Lithuanian households by subcategory - income. Sample period 2011.01-2025.05.	107

Table 15. Balance statistics means of Lithuanian households by subcategory - education. Sample period 2011.01-2025.05.....	109
Table 16. Balance statistics means of Lithuanian households by subcategory - sex. Sample period 2011.01-2025.05.....	111
Table 17. Correlation of balance statistic differences between questions. Subcategory - age.....	115
Table 18. Correlation of balance statistic differences between questions. Subcategory - income.....	115
Table 19. Correlation of balance statistic differences between questions. Subcategory - education.....	116
Table 20. Correlation of balance statistic differences between questions. Subcategory - sex.....	116
Table 21. Accuracy of quantified Lithuanian consumer inflation perceptions.....	118
Table 22. Accuracy of quantified euro area consumer inflation expectations.....	119

LIST OF FIGURES

Figure 1. Aggregate density function of inflation expectations, normal distribution.	51
Figure 2. Lithuania YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.....	63
Figure 3. Latvia YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.....	63
Figure 4. Estonia YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.....	64
Figure 5. Poland YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.....	64
Figure 6. Euro area YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.....	64
Figure 7. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.....	68
Figure 8. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.....	69
Figure 9. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.....	69
Figure 10. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.....	70
Figure 11. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.....	70
Figure 12. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory - age.	104
Figure 13. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - age.	104
Figure 14. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - age.....	105
Figure 15. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - age.	105

Figure 16. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory - income.	107
Figure 17. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - income.	107
Figure 18. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - income.	108
Figure 19. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - income.	108
Figure 20. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory – education.	109
Figure 21. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - education.	110
Figure 22. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - education.	110
Figure 23. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - education.	110
Figure 24. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory – sex.	111
Figure 25. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - sex.	112
Figure 26. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - sex.	112
Figure 27. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - sex.	112
Figure 28. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.	139
Figure 29. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.	139
Figure 30. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.	140
Figure 31. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.	140

Figure 32. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.....	141
Figure 33. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).....	141
Figure 34. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).....	142
Figure 35. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).....	142
Figure 36. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).....	143
Figure 37. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).....	143
Figure 38. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.....	144
Figure 39. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.....	144
Figure 40. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.....	145
Figure 41. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.....	145

Figure 42. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation ($\pi_{p,t}$) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.....	146
Figure 43. PVAR FE OLS model impulse response functions when impulse is CONS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.....	158
Figure 44. PVAR FE OLS model impulse response functions when impulse is RGDP_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.....	159
Figure 45. PVAR FE OLS model impulse response functions when impulse is GS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	160
Figure 46. PVAR FE OLS model impulse response functions when impulse is LOANS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.....	161
Figure 47. PVAR FE OLS model impulse response functions when impulse is PI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	162
Figure 48. PVAR FE OLS model impulse response functions when impulse is UN_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	163
Figure 49. PVAR FE OLS model impulse response functions when impulse is BS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	164
Figure 50. PVAR FE OLS model impulse response functions when impulse is DEPOSITS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.....	165
Figure 51. PVAR FE OLS model impulse response functions when impulse is WAGES_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.....	166
Figure 52. PVAR FE OLS model impulse response functions when impulse is i_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	167
Figure 53. PVAR FE OLS model impulse response functions when impulse is ENERGY_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.....	168

Figure 54. PVAR FE OLS model impulse response functions when impulse is CCI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	169
Figure 55. PVAR GMM system model impulse response functions when impulse is CONS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	170
Figure 56. PVAR GMM system model impulse response functions when impulse is RGDP_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	171
Figure 57. PVAR GMM system model impulse response functions when impulse is GS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	172
Figure 58. PVAR GMM system model impulse response functions when impulse is LOANS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	173
Figure 59. PVAR GMM system model impulse response functions when impulse is PI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	174
Figure 60. PVAR GMM system model impulse response functions when impulse is UN_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	175
Figure 61. PVAR GMM system model impulse response functions when impulse is BS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	176
Figure 62. PVAR GMM system model impulse response functions when impulse is DEPOSITS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	177
Figure 63. PVAR GMM system model impulse response functions when impulse is WAGES_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	178
Figure 64. PVAR GMM system model impulse response functions when impulse is i_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	179
Figure 65. PVAR GMM system model impulse response functions when impulse is ENERGY_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	180
Figure 66. PVAR GMM system model impulse response functions when impulse is CCI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	181

Figure 67. PVAR FE OLS model impulse response functions when impulse is PI_EXP1_YOY (quantified inflation expectations with scaling parameter as current inflation level). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	182
Figure 68. PVAR FE OLS model impulse response functions when response is PI_EXP1_YOY (quantified inflation expectations with scaling parameter as current inflation level). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	183
Figure 69. PVAR FE OLS model impulse response functions when impulse is PI_EXP2_YOY (quantified inflation expectations with scaling parameter as running average of past inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	184
Figure 70. PVAR FE OLS model impulse response functions when response is PI_EXP2_YOY (quantified inflation expectations with scaling parameter as running average of past inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	185
Figure 71. PVAR FE OLS model impulse response functions when impulse is PI_EXP3_YOY (quantified inflation with scaling parameter as quantified perceived inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	186
Figure 72. PVAR FE OLS model impulse response functions when response is PI_EXP3_YOY (quantified inflation expectations with scaling parameter as quantified perceived inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.	187
Figure 73. Forecast Error Variance Decomposition for real consumption YoY change (CONS_YOY), real GDP YoY change (RGDP_YOY), government spending YoY change (GS_YOY), household loans YoY change (LOANS_YOY).	188
Figure 74. Forecast Error Variance Decomposition for YoY inflation (PI_YOY), unemployment rate YoY change (UN_YOY), balance statistics of consumer inflation expectations YoY change (BS_YOY), household deposits YoY change (DEPOSITS_YOY).	189
Figure 75. Forecast Error Variance Decomposition for wages YoY change (WAGES_YOY), interest rate YoY change (i_YOY), energy prices YoY change (ENERGY_YOY), consumer confidence index YoY change (CCI_YOY).	190

INTRODUCTION

Relevance of topic. The study of inflation expectations has gained renewed prominence in macroeconomic research and policy debates, particularly following the post-pandemic surge in inflation and the accompanying increase in macroeconomic uncertainty. Inflation expectations play a central role in shaping economic behavior, influencing household consumption and saving decisions, wage bargaining, and firms' pricing strategies. As emphasized in both classical and modern macroeconomic frameworks, expectations constitute a key transmission channel through which monetary policy affects real economic outcomes (Orphanides and Williams, 2005; Woodford, 2003). Consequently, the anchoring of inflation expectations has become a core objective of central banks.

Despite their theoretical importance, the empirical performance and economic relevance of inflation expectations, particularly those formed by consumers, remain contested. A growing body of evidence documents that consumer inflation expectations are often biased, highly heterogeneous, and weakly forward-looking, raising questions about their predictive accuracy and their role in macroeconomic dynamics (Coibion and Gorodnichenko, 2015; Rudd, 2021; Weber, Coibion and Gorodnichenko, 2023). Recent studies using household-level microdata and randomized controlled trials further show that expectations respond strongly to salient price changes, information treatments, and perceived inflation uncertainty, while remaining only imperfectly anchored to central bank targets (Duca, Kenny and Reuter, 2021; Huber, Minina and Schmidt, 2023; Kostyshyna and Petersen, 2024). These findings underscore that how inflation expectations are measured is inseparable from how they are interpreted and used in policy analysis.

What is more, consumer inflation expectations in the Baltic countries have not been adequately addressed in academic literature. Often the adoption of euro is cited as the reason for not including these countries in research samples. Thus, this study also seeks to fill a gap in the literature by exploring the quantification and accuracy of consumer inflation expectations in Lithuania, Latvia, and Estonia.

A central element of this dissertation is the application and evaluation of the Carlson–Parkin (1975) method, which remains the most widely used technique for transforming qualitative survey data on inflation perceptions and expectations into quantitative estimates. The enduring appeal of the CP method lies in its simplicity and its ability to generate time series of expectations even when respondents only indicate the expected direction of price changes. For institutions such as the European Commission and national

statistical agencies, the method has provided a practical tool for monitoring consumer attitudes across large and diverse populations. However, its widespread use has also prompted critical discussion. The validity of CP-derived measures depends heavily on assumptions about the distribution of underlying expectations, the symmetry of indifference intervals, and the stability of scaling factors. These assumptions, while convenient, are not innocuous: deviations from normality, shifts in consumer sensitivity to prices, or heterogeneity across groups can all distort the resulting estimates (Lolić and Sorić, 2017; Rutkowska, Szyszko and Pietrzak, 2023).

The standard Carlson–Parkin assumptions may not be fully applicable in the context of small, open Baltic economies. These economies tend to be more exposed to external price and demand shocks, which can contribute to asymmetries or increased dispersion in consumer perceptions of inflation. Consumers may also assign greater weight to price increases than to price decreases, potentially resulting in right-skewed or heavy-tailed expectation distributions. In addition, structural shifts, including euro adoption and periods of elevated inflation, may affect the stability of the scale parameters typically assumed in the CP framework. What is more, recent cross-country studies show that the formation and behavior of inflation expectations vary markedly across countries and regions, suggesting that findings derived from larger euro area economies cannot be automatically generalized to other countries (Szyszko and Rutkowska, 2019; Kliber et al., 2023). Together, these factors suggest that the applicability of the standard CP assumptions in the Baltic context warrants careful empirical evaluation, thereby motivating the methodological assessment undertaken in this dissertation.

This study takes up these methodological concerns directly. By applying the CP framework to Baltic survey data, I test the robustness of the method’s assumptions in economies that differ from the larger euro area countries usually studied. Small, open, and historically transitional, the Baltic states provide a stringent test case for whether the CP method can generate reliable measures of inflation expectations outside the core of the euro area. Moreover, by relaxing distributional assumptions and experimenting with alternative scaling parameters, this study contributes to the methodological debate on how best to quantify qualitative survey responses. In doing so, it addresses the dual challenge faced by researchers and policymakers: (1) the need for comparable indicators across countries and (2) the importance of tailoring methods to specific national contexts.

The problem and research object. The central problem explored in this thesis is the challenge of accurately quantifying consumer inflation expectations using probabilistic and statistical approaches. The Carlson-

Parkin (CP) method, widely used for converting qualitative survey responses into quantitative estimates, often assumes a normal distribution of consumer expectations. However, research has questioned the validity of this assumption, suggesting that alternative distributions might better capture the asymmetric nature of consumer expectations (Batchelor and Orr, 1988; Lolic and Soric, 2017; Rutkowska, Szyszko and Pietrzak, 2023). The object of this research is therefore twofold. First, it is to critically evaluate the robustness of CP-based quantification methods by testing alternative distributional assumptions, scaling choices, and aggregation procedures. This includes assessing whether refinements improve the fit and predictive value of expectations in both the Baltic states and the wider sample. Second, it is to examine the economic role of consumer expectations by situating quantified measures within broader macroeconomic relationships, including their interaction with inflation, consumption, unemployment, and output.

By pursuing this dual focus, the dissertation addresses the methodological shortcomings of expectation quantification (Chapters 2–5), applies refinements empirically to the Baltic states as under-researched economies (Chapter 3), tests their macroeconomic relevance in an EU-wide panel setting (Chapter 4), and incorporates heterogeneity across socio-demographic groups to improve accuracy (Chapter 5). In this way, the study contributes to both the technical refinement of expectation measurement and to the empirical understanding of how consumer expectations influence, and are influenced by, inflation dynamics in diverse economic environments.

Goal and objectives. The main goal of this research is to test the accuracy and applicability of inflation expectations measurements by refining existing quantification methods and exploring new approaches. This goal is driven by the need to provide policymakers with reliable data on consumer inflation expectations, which is essential for effective monetary policies in a diverse economic environment. The following specific objectives are formulated:

1. To critically evaluate the applicability of the Carlson-Parkin method and its traditional assumption of a normal distribution: The dissertation aims to extend the literature by exploring alternative statistical distributions, such as skewed, leptokurtic, and asymmetric distributions, to determine if they provide a better fit for consumer expectations data.
2. To examine the impact of euro adoption on the quantification of consumer inflation expectations in the Baltic countries. The analysis investigates whether the transition to the euro had any impact on the optimal procedure for quantifying consumer inflation expectations.

3. To test the forward-lookingness and predictive power of both quantified consumer inflation expectations and balance statistics of consumer responses.
4. To examine the macroeconomic role of consumer expectations in the European Union. Using a panel VAR framework for 26 EU countries, the research explores the interaction between quantified expectations, inflation, GDP, unemployment, and consumption, thereby assessing the how different CP configurations affect the results.
5. To investigate the heterogeneity of inflation expectations across socio-demographic groups. By disaggregating survey responses by age, income, education, and gender, the study evaluates whether subgroup-specific quantification improves accuracy and what these differences reveal about the formation of expectations in diverse populations.

Research methods. The core methodology revolves around the application and enhancement of the Carlson-Parkin (CP) method, which translates qualitative survey responses into quantitative measures of inflation expectations. While the traditional CP framework assumes a normal distribution of responses, this study evaluates its robustness by testing alternative distributional assumptions, including skewed and leptokurtic forms, and by exploring the effects of different scaling choices. These refinements allow for a more flexible treatment of consumer expectations, particularly in contexts where the canonical assumptions are unlikely to hold.

Beyond this central focus, the study relies on a range of complementary methods. Chapters 1-3 rely on systematic literature review, descriptive statistics, graphical analysis, and unit root tests to situate the CP method within the broader field of expectation measurement and to evaluate its empirical properties. Ordinary least squares regressions are used to test the predictive performance of quantified expectations against realized inflation. For the EU-wide analysis in Chapter 4, the dissertation applies a panel vector autoregression (PVAR) framework to explore the interaction of consumer expectations with inflation, GDP, unemployment, and consumption across 26 member states. Finally, Chapter 5 extends the methodological scope by applying subgroup-based quantification of inflation expectations. Survey responses are disaggregated by age, income, education, and gender, and the CP method is applied within each subgroup before re-aggregation with population weights.

Significance, novelty, and contribution of the research. This dissertation contributes to the literature on inflation expectations in several interrelated ways. First, it challenges the conventional assumption of normality in the Carlson–Parkin method by systematically testing alternative

distributional forms and scaling parameters. Although the CP method has been applied extensively in international datasets, only a limited number of studies have examined its robustness in small, open economies (Berk, 1999; Lyziak, 2003; etc.), and even fewer (Lolic and Soric, 2017; Rutkowska, Szyszko and Pietrzak, 2023) have compared alternative specifications in detail. By refining the methodology and highlighting the sensitivity of quantified expectations to modelling choices, the research advances the debate on how best to extract information from qualitative surveys. Second, the dissertation provides new empirical evidence from the Baltic states, namely, Lithuania, Latvia, and Estonia, which are frequently underrepresented from cross-country studies. By applying refined quantification methods to these economies, the study documents distinctive features of expectation formation in transitional and highly open contexts, including higher volatility and shorter forecasting horizons. Third, the research extends the analysis to a broader European setting through a panel VAR framework covering 26 EU countries. The novelty of this part lies not in the use of the econometric technique itself, but in the way consumer expectations were incorporated. By quantifying survey data with alternative specifications of the Carlson–Parkin method and comparing them against balance statistics, the study demonstrates how methodological choices affect the estimated macroeconomic role of expectations. The results reveal significant cross-country heterogeneity and confirm that while consumer expectations can affect short-term consumption and inflation, their influence is uneven and sensitive to the way they are measured. This adds a novel dimension to the debate on expectations by linking methodological robustness with cross-country empirical evidence. Finally, the dissertation incorporates heterogeneity into the quantification of expectations by analyzing subgroups defined by age, income, education, and gender. This subgroup-based approach demonstrates that disaggregated quantification can substantially improve accuracy and provides insights into how demographic factors shape inflation perceptions and expectations.

Practical significance. The practical significance of this research lies in its ability to improve how consumer inflation expectations are measured and interpreted for policymaking purposes. By identifying which quantification methods and configurations yield the most accurate results, the dissertation provides guidance for central banks and statistical institutions that rely on survey-based indicators. In particular, the study shows that results are sensitive to distributional assumptions, scaling parameters, and aggregation choices, implying that policymakers should treat quantified expectations as informative but method-dependent indicators rather than objective measures.

Defended statements

1. The conventional assumption of normally distributed consumer expectations in the Carlson–Parkin method is not universally valid; alternative distributional forms can provide a more accurate quantification of inflation expectations. Choice of scaling parameter does, however, matter more in terms of the accuracy of quantified consumer responses.
2. Quantified consumer inflation expectations derived from survey data exhibit limited forward-lookingness and predictive accuracy, yet they can outperform balance statistics in explaining future inflation dynamics.
3. Consumer inflation expectations are associated with measurable variation in macroeconomic developments of the European Union, exerting measurable effects on consumption, unemployment, and inflation within a panel VAR framework.
4. Incorporating socio-demographic heterogeneity in the quantification of inflation expectations significantly improves measurement accuracy and reveals systematic differences in expectation formation across age, income, education, and gender groups.
5. The methodological choices made in quantifying qualitative survey data, namely, distributional assumptions, scaling parameters, and aggregation rules, have substantive consequences for both academic research and monetary policy, as they shape the estimated role of expectations in economic outcomes.

Structure of the thesis. The study consists of five chapters. Chapter 1 reviews the theoretical and empirical literature on inflation expectations, while Chapter 2 focuses on the methodology of quantification with emphasis on the Carlson–Parkin framework and its alternatives. Chapter 3 applies these methods to the Baltic states, examining euro adoption, forward-lookingness, and predictive accuracy. Chapter 4 broadens the scope to a panel of 26 EU countries using a panel VAR to assess the macroeconomic role of consumer expectations and the effects CP method application has on the results. Chapter 5 investigates heterogeneity across demographic groups, showing how subgroup-based quantification improves accuracy.

1. THEORETICAL BACKGROUND AND LITERATURE

REVIEW ON INFLATION EXPECTATIONS

Since expectations play a central role in modern macroeconomics yet remain difficult to observe and quantify, the literature on this topic is broad and contested. This chapter therefore reviews the evolution of expectations in economic theory, from early Keynesian and adaptive frameworks to rational and bounded rational models. It also examines the main approaches to measuring inflation expectations with particular attention to the strengths and limitations of each. Finally, the chapter considers methodological debates on quantification techniques, especially the Carlson–Parkin method, in order to identify the unresolved issues that motivate the empirical and methodological contributions of this dissertation. The discussion is structured to highlight those strands of the literature that are most relevant for consumer inflation expectations and for the quantification of qualitative survey data.

1.1. The Role of Expectations in Economic Thought

In early economic modelling, the role of expectations was considered rather peripheral, due to the fundamental assumptions of classical and early neoclassical economic models. These models proposed, that the self-adjusting nature of markets and the assumption that economic agents make decisions based on full information, would allow them to make relatively clear predictions about the future (Salvatore, 2014). Although, the development of modern macroeconomics theory challenged this assumption, leading scholars to reconsider the role of expectations in understanding the behavior of agents in uncertain economic environments.

John M. Keynes (1936) was among the first scholars to address limitations in the assumption of perfect foresight and recognize the importance of expectations. Keynes (1936) theorized that in uncertain environments, the behavior of economic agents is determined by their expectations, rather than fixed economic rules. In this sense, the author introduced the concept of animal spirits that described psychological factors, which influence expectations and can lead agents to volatile investment behavior. According to Keynes (1936), it is the investors' expectations that propel economic booms or declines, therefore forming economic cycles, which are not necessarily aligned with the primary assumptions of economic modelling. Evidently, focus on the role of expectations in economic modelling marked the beginning of a growing scholarly interest in the dynamics of expectations formation and its influence on macroeconomic outcomes. Over time, varying hypotheses

emerged, leading to the development of *adaptive expectations*, *rational expectations*, and *non-rational* or *bounded rationality* expectations theories.

Adaptive Expectations. The hypothesis of adaptive expectations can be attributed to Phillip Cagan (1956), who formally introduced this model in his research on hyperinflation. The author argued that individuals form their expectations for future inflation by taking into account past inflation rates, and therefore adjust their expectations over time (Cagan, 1956). Notably, this approach assumed that individuals would gradually modify their beliefs as a response to observed errors in their past forecasts. According to Cagan (1956), the gradual adjustment reflects a learning process where past outcomes inform, but do not fully determine future beliefs of an economic agent. This fundamental principle of adaptive expectations was later adapted in the Phillips Curve framework (1958), although in its original formulation a consistent inverse relationship between inflation and unemployment was suggested.

Nevertheless, the theoretical basis of the Phillips curve was challenged by Milton Friedman (1968) and Edmund Phelps (1967), who argued that it neglected the importance of inflation expectations. Building upon this argument, Phelps (1967) emphasized that higher inflation could not be permanently traded for lower unemployment, as it would break down, once economic agents adapted their expectations. In other words, higher inflation could not be systematically used as a monetary policy tool to maintain lower unemployment in the long run. This notion was further developed by M. Friedman (1968), who introduced the concept of the *natural rate of unemployment*. It allowed him to further assert the argument that monetary policy could not systematically reduce unemployment below this natural rate without consequently accelerating inflation in the long run. Friedman's work has underlined the limits of adaptive expectations with regard to explaining long-term economic dynamics. Although adaptive expectations could explain short-term adjustments, it was essentially based on historical data, thus neglecting future information (Friedman, 1968). Limitations of adaptive expectations became even more evident when Keynesian models were challenged by apparent stagflation in the 1970s. It was observed that adaptive expectations cannot account for high inflation during the time of high unemployment (Friedman, 1968; Phelps, 1967; 1972), thus leading scholars to reconsider the complexity and dynamics of expectations formation.

Rational Expectations. The hypothesis of rational expectations, first introduced by John Muth (1961), proposed that individuals' expectations about the future are not solely determined by past information. The author argued that individuals form their future expectations based on all available

information, including their own understanding of economic models and trends. Moreover, this approach presupposed that individuals act as rational agents, and therefore form their expectations by utilizing all relevant information without making systematic errors in their forecasts (Muth, 1961). In other words, the assumption of full information suggested that individuals' expectations were accurate and would align with the predictions of theoretical models.

Hypothesis of rational expectations was also supported by Robert Lucas (1972), Thomas Sargent (1979), and other scholars of the New Classical School, who criticized the notion of reliance on past-information. Lucas (1972) argued that traditional Keynesian models could not account for the forward-looking behavior of economic agents, as their expectations would adjust in response to anticipation of these changes. According to Lucas (1976), such models as the Phillips curve could not accurately predict the effects of policy changes, if it did not account for changes in expectations. This essentially challenged the theoretical premise and predictive power of prevailing past-information based models. *Lucas Critique* posited that the effectiveness of monetary policy can be influenced by anticipations of those changes, therefore models used for policy evaluation, must consider how the policy will alter the expectations and, consequently, behavior of economic agents (Lucas, 1976). This assumption had a fundamental impact on the macroeconomic theory and has led scholars to theorize that real economic outcomes can be influenced only by unanticipated policy changes (Sargent and Wallace, 1975). The approach of rational expectations inherently shifted the perception of expectations role, leading to the development of models that could account for changes in expectations. Based on the hypothesis of rational expectations, the New Classical approach suggested that fluctuations in output and employment are driven by real shocks, rather than monetary or demand-side shocks. Sargent (1979) argued that the effectiveness of policy changes can be considerably affected by the changes in expectations. Therefore, the scope of discretionary monetary policy effects was considered to be very limited, as economic agents would anticipate changes in monetary policy, thus neutralizing the effects of such policies on the real economic outcomes.

Although the theory of rational expectations fundamentally influenced the field of macroeconomic research, it has not escaped the criticism for its core premise of human rationality. Economists like Herbert Simon (1955), George Akerlof (1970) and Joseph Stiglitz (1972;1973) argued that the assumption of individuals' abilities to process full information and make unbiased forecasts is not entirely realistic. Subsequently, this consideration

led to the development of alternative models that could account for the factor of limited human rationality.

Non-Rational Expectations. Hypothesis of non-rational expectations emerged as an approach to address the limitations of both adaptive and rational expectations. H. Simon (1955), who first introduced the concept of bounded rationality, argued that individuals may not have neither the means, nor the cognitive capacity to sufficiently process all available information and make optimal decisions accordingly. This hypothesis was rooted in the assumption that economic agents can be influenced by a number of factors, that do not necessarily lead to optimal future forecasts, especially in uncertain economic environments. Simon (1955) proposed that individuals would rather utilize rules of thumb or heuristics that lead to *satisficing* rather than optimal economic decisions. The approach of bounded rationality essentially suggested that cognitive limitations of individuals can lead to the systematic errors or biases in their forecasts, making them less reliable.

The framework of non-rational expectations was further developed by behavioral economists like Daniel Kahneman and Amos Tversky (1979). These authors argued that individuals' expectations and economic decision-making processes can be significantly affected by such factors as *framing effects*, *loss aversion*, and *overconfidence*. Similarly, Robert J. Shiller (2000) outlined that, due to various cognitive biases, individuals may form expectations that notably deviate from the predictions of the rational expectations model. In this sense, Shiller (2000) noted that investors may exhibit herding behavior and follow the expectations of others instead of relying on their own predictions of changes in the market. Ultimately, this approach implied that economic agents' behavior can be driven by overly optimistic or pessimistic expectations, that can cause asset bubbles or lead to crashes in the market.

Models of non-rational expectations also addressed the factor of incomplete information. According to N. Gregory Mankiw and Ricardo Reis (2002), economic agents are considered to have the access to some but not all relevant information, leading them to form only partially informed expectations. This approach also helped to explain such occurrences as sticky prices and menu costs, where firms would adjust prices infrequently due to uncertainty about the future inflation or demand (Mankiw and Reis, 2002). The hypothesis of rational expectations was further criticized by Athanasios Orphanides, who argued that the policymakers themselves may also have incomplete information, leading them to form expectations that deviate from rational modelling forecasts (Orphanides, 2001). Evidently, this led to the development of new research, in which subjecting policymakers to the same

cognitive and information limitations as private agents, resulted in inaccurate expectations and policy errors. Thus, by incorporating the factor of information asymmetry, the non-rational expectations models allowed a more accurate representation of expectations formation dynamics.

1.2. Inflation Expectations Measurement and Effects

This focus in this subsection is twofold. Firstly, it aims to briefly outline how inflation expectations as well as perceptions are measured. Secondly, it intends to establish the importance of inflation expectations by discussing both the hypothesized effects of it as well as a recent debates in the academic literature.

1.2.1. Importance of Inflation Expectations

In modern macroeconomic frameworks, the role of expectations is considered to be a fundamental component in shaping economic outcomes and is explicitly incorporated into macroeconomic models such as Phillips curve. Notably, inflation expectations are recognized to have significant influence on a wide range of economic decisions. Particularly, in relation to monetary policy planning, where inflation expectations can both influence and be influenced by the behavior of economic agents.

The argument for the importance of inflation expectations stems from their self-fulfilling nature, essentially implying that if economic agents expect higher inflation, they may adjust their behavior in such ways that can contribute to the actual increase in inflation. This principle of self-fulfilling prophecy is illustrated in models such as Phillips curve, that describes the relationship between unemployment and inflation. It asserts the notion that firms, anticipating a rise in costs, may increase their prices pre-emptively, whereas workers expecting an increase of living costs, may demand higher wages to maintain their purchasing power. This essentially implies that anticipation of inflation leads economic agents to take preventative measures that prompt actual inflationary process, therefore validating their initial expectations and creating a feedback loop. Hence, inflation expectations management or *anchoring* is considered a crucial task of central banks in ensuring effective monetary policy. As outlined by B. S. Bernanke (2007), when inflation expectations are well-anchored, economic agents trust that central bank will maintain price stability over the long term, and this trust helps to prevent excessive volatility in inflation rates. Moreover, if inflation expectations become unanchored, it can considerably destabilize economic

environment by prompting either inflationary (or deflationary) processes. To prevent fluctuations in the market and stabilize inflation, central banks aim to influence the behavior of economic agents by shaping their expectations through communication and policy announcements, i.e. *forward guidance* (Woodford, 2003; Blinder, Ehrmann, Fratzscher, De Haan and Jansen, 2008). Accordingly, the most challenging task of monetary policy makers is to ensure that inflation expectations remain well-anchored, despite the short-term fluctuations or economic uncertainty. Thus, measuring inflation expectations helps central banks to make more accurate predictions of future inflation trends and maintain long-term economic stability.

1.2.2. Measuring Different Types of Inflation Expectations

Inflation expectations are categorized into *market-based*, *business-based*, and *consumer-based* expectations, thus reflecting the perspectives of different economic agents. Accordingly, the primary methods used to measure inflation expectations can be grouped into *survey-based measures* and *econometric models*. These methods provide different valuable insights into the dynamics of inflation expectations and their formation.

Market-based inflation expectations. Market-based inflation expectations define the rate of inflation anticipated by financial markets and are derived through the prices of inflation-indexed bonds and derivatives. Two primary instruments that are typically used to measure market-based inflation expectations are the *breakeven inflation rate* and *inflation swaps*. Breakeven inflation rate (BEIR) represents the average annual inflation rate that investors expect over the life of the bond and is calculated as the difference between the yields on nominal government bonds and inflation-linked bonds of the same maturity. In this sense, inflation expectations are reflected through the behavior of investors, whose anticipation of higher inflation leads them to demand higher yields on nominal bonds in order to compensate for anticipated erosion of purchasing power (Campbell and Shiller, 1996). According to R. S. Gürkaynak, B. Sack and J. H. Wright (2010), market-based inflation expectations reflect the collective judgement of sophisticated investors who are actively trading in financial markets, making them a reliable proxy for inflation expectations. Therefore, one of the key advantages of market-based inflation measures is that they provide a continuously updated forward-looking perspective, which is based on actual financial transactions. Another measure of market-based inflation expectations is inflation swaps, used by investors to hedge against inflation risk. In this sense, inflation swaps can reflect markets' inflation expectations through the fixed rate (*fixed leg*) of

swaps offers. Additionally, inflation swaps can also provide exposure to inflation as an asset class, which allows investors to trade inflation-linked securities at a predetermined rate, thus reflecting distribution of inflation expectations. Thus, measures such as breakeven inflation rate and inflation swaps are considered to be more accurate than survey-based measures, as they are derived from real-time financial data. However, market-based measures also have several limitations that can artificially affect the inflation rate. For instance, in periods of economic uncertainty, investors may turn to more secure assets such as nominal bonds, leading to a decline in their yields and thus lowering the breakeven inflation rate. Hence, this artificial decrease would provide a possibly misleading view of investors' inflation expectations, making it inaccurate. Another limitation of market-based measures, as noted by J. H. Christensen and J. M. Gillan (2012), is the lack of perspective of households and businesses, whose consumption and investment decisions can influence inflation. Overall, although market-based inflation expectations are considered a valuable measure, they reflect a relatively limited scope, providing only the perspective of economic agents that are actively trading in financial markets.

Business-based inflation expectations. Business-based inflation expectations reflect the anticipations of different firms across various economic sectors. Inflation expectations of businesses are based on such factors as supply-side costs, price-setting, wage demands and other economic conditions. Thus, the dynamics of firms' pricing and investment decisions can reflect how they expect future inflation to evolve (Mankiw and Reis, 2002). However, although businesses form their expectations by taking into account the forecasts of central banks, the principle of self-fulfilling prophecy applies to business-based expectations as well. Businesses may pre-emptively increase their prices due to anticipation of rising supply-costs or, and in contrast, lower their prices in anticipation of lower demand or falling costs. In both cases, businesses' pricing decisions that are based on anticipated changes of inflation rate can influence the actual inflation. Moreover, businesses' anticipations of changes in inflation can influence their investment and wage-setting decisions that subsequently impact broader economic development and stability.

The input for business-based inflation expectations is typically gathered through surveys conducted in various-sized businesses across different industries. Notable example of such surveys is the Atlanta Federal Reserve's Business Inflation Expectations Survey that targets businesses across different sectors in the states of Sixth Federal Reserve District. In this survey businesses are asked about expected economic pressures, changes in their pricing and

their anticipations of changes in inflation for the upcoming year. Thus, data gathered through this survey provides the Federal Reserve Bank with a broader overview that helps to monitor the inflationary trends. However, it is important to note that businesses can face different economic conditions such as supply-demand pressures or labor market fluctuations that are sector-specific, thus affecting only certain industries. Thus, one of the considerable limitations of this measure is the aggregation of survey data. According to C. D. Carroll (2003), aggregating the data of businesses' inflation expectations across different sectors can obscure important differences that affect overall inflation dynamics. However, despite its limitations, business-based inflation expectations are considered a particularly important measure, that allows central banks to make more accurate forecasts of inflationary trends and adjust their monetary policy.

Consumer-based inflation expectations. Consumer-based inflation expectations reflect the perspective of households and are based on their experiences with prices for goods and services such as food, energy and housing. Due to their direct influence on shaping consumption and saving behaviors of households, consumer-based expectations are considered to be a critical factor in inflation dynamics. The anticipation of increasing prices, may prompt the consumption, leading to higher aggregate demand and fueling the inflationary process. Similarly, the anticipation of increasing living costs, may lead workers to demand higher wages, resulting in wage-price spirals and increasing inflationary pressures (Orphanides and Williams, 2005; Bernanke, 2007). Conversely the anticipation of decreasing prices, may delay consumption, lowering demand and potentially triggering deflationary dynamics. Evidently, this highlights the self-fulfilling nature of expectations formation and further emphasizes the importance of anchoring consumers' inflation expectations to ensure effective economic policy.

The input for consumer-based inflation expectations is typically gathered through surveys. One of the most widely cited surveys is the University of Michigan's Survey of Consumers, which asks respondents about their inflation expectations over the next year and the next five to ten years. This monthly survey gathers expectations from a nationally representative sample of U.S. households using primarily quantitative questions. Respondents are asked the following questions: (1) *By about what percent do you expect prices to go (up/down) on the whole, during the next 12 months?* (2) *By about what percent per year do you expect prices to go (up/down) on average, during the next 5 to 10 years?* These questions enable statisticians to obtain quantitative forecasts from consumers, providing a concrete measure of how consumers anticipate the future prices to develop. The advantage of these quantitative

questions is that they produce specific data, allowing for a more precise aggregation and analysis of inflation expectations across different demographic groups and over time.

However, one challenge with such quantitative questions is the potential for measurement error due to respondents' limited financial literacy or lack of understanding of the concept of inflation. Research shows that consumers, particularly those with lower levels of education or financial sophistication, often struggle to provide accurate numerical estimates of future inflation (Bruine de Bruin, Manski, Topa and Van der Klaauw, 2010). Furthermore, research suggests that the answers of respondents can be influenced by salient recent price changes, particularly shocks in fuel or food prices, resulting in overestimation of inflation rates (Armantier, Nelson, Topa, Van der Klaauw and Zafar, 2016).

Moreover, these quantitative measures can be skewed by outliers. Some respondents provide extremely high or low inflation expectations, which can heavily distort aggregate measures. Researchers often deal with this issue by using median expectations rather than means, as medians are less affected by outliers. Another approach to address this issue is limiting the maximum and minimum values allowed as responses. Despite these limitations, the Michigan Survey remains a valuable tool for capturing consumer inflation expectations in a straightforward, numerical format.

In contrast to the University of Michigan's quantitative approach, the European Commission's Harmonised EU Programme of Business and Consumer Surveys relies more heavily on qualitative responses. This survey is conducted across European Union member states and aims to gauge consumers' perceptions of inflation, economic conditions, and personal financial situations. In addition to the quantitative questions about expected inflation over the next 12 months, questions of qualitative nature are asked. Specifically, respondents are asked: *How do you expect the prices in your country to change over the next 12 months: (1) increase more rapidly; (2) increase at the same rate; (3) increase at a slower rate; (4) stay about the same; (5) fall; (6) don't know.* This question allows for a qualitative assessment of inflation expectations, providing insights into the direction and pace of expected price changes, rather than exact numerical forecasts. Such qualitative data is useful in contexts where consumers may struggle to provide precise inflation estimates or quantitative responses are prone to outliers. By giving respondents options to select from, the survey reduces the cognitive burden associated with quantitative forecasting, making it easier for individuals to express their expectations.

However, while qualitative responses might be suitable in cases when a broad sentiment of consumers is in question, such responses lack in precision. The responses provide information about whether consumers expect inflation to rise or fall, but they do not capture the magnitude of these expectations. This lack of precision can be problematic for policymakers who need to understand not only whether inflation is expected to rise but by how much. Additionally, converting qualitative responses into quantitative measures often involves assumptions and statistical techniques that can introduce errors or bias into the data. These issues motivate the methodological discussion in Chapter 3 regarding quantification procedures.

Overall, both qualitative and quantitative approaches are valuable for understanding consumer inflation expectations, and each offers unique insights. However, consumer-based inflation expectations have several limitations. Researchers note that, compared to market-based and business-based measures, consumer inflation expectations are often more volatile and thus considered less reliable (Bruine de Bruin et al., 2010; Armantier et al., 2016). According to Armantier et al. (2016), consumers' expectations are based on their personal experiences with prices of volatile items like energy and food items, thus their expectations can be influenced by significant short-term fluctuations, despite the stability of underlying inflation trends. Similarly, Bruine de Bruin et al. (2010) argue that the factor of limited information, especially in comparison to participants of financial markets and businesses, can lead consumers to systematic biases in their forecasts. Evidently, such overestimation of future inflation can lead consumers to make irrational financial decisions which may increase market volatility. Despite these limitations, consumer-based inflation expectations play a crucial role in shaping consumption behavior and wage demands, thus this measure provides valuable insights into future price changes.

1.2.3. Econometric Approach to Measuring Expectations

An alternative approach to measuring inflation expectations relies on modelling historical data and economic variables to forecast future inflation. These models can range from simple time-series models, such as autoregressive integrated moving average (ARIMA) models, to more complex structural models that incorporate various macroeconomic factors, such as output gaps, labor market conditions, and monetary policy variables. Econometric models have several advantages compared to survey-based measures. First, they can be tailored to specific economic conditions, allowing for a more nuanced and accurate forecast of inflation. Second, they provide a

systematic and objective method for forecasting inflation, based on well-established economic relationships.

Such approach, however, does not reflect the true expectations of the economic agents. Rather, the models are mostly backward-looking, relying on historical data to predict future inflation, which can be problematic in volatile economic environments. What is more, econometric models are only as good as the data and assumptions that underlie them. If the model is misspecified or fails to account for important variables, the resulting inflation expectations may be inaccurate.

Naturally, a question arises whether survey based measures of evaluating inflation expectations provide any benefit when compared to econometric approaches. Specifically, which type of expectations measurement provides better forecasts of future price movements and whether inflation expectations improve inflation forecast models. The literature on this topic is not straightforward. Some research carried out finds that survey-based expectations are more accurate when compared to empirical models (Faust and Wright, 2013; Grothe and Meyler, 2017). Also, some research suggests that survey based expectations are an important covariate when forecasting inflation (Clark and Doh, 2014; Groen, Paap, and Ravazzolo, 2013). However, other researchers have found that even simple ARMA (1,1) model can outperform expectations of both professionals and consumers (Berge, 2018). Overall, economists warn that the performance of inflation forecast models is not stable over time and is highly dependent on the period analyzed and inflation dynamics during it (Fisher, Liu, and Zhou (2002); Stock and Watson (2010)). Therefore, it is important to check various time-frames and samples when investigating predictive power of inflation expectations.

1.2.4. Debate on the Effects of Inflation Expectations

While there are plenty of arguments in the academic literature supporting the claim that expectations play a crucial role in determining actual inflation, the empirical evidence supporting this relationship is far from robust. Rudd (2021) published a paper that sparked a substantial debate between economists as his research questioned the above-mentioned claims.

In this paper, Rudd (2021) questions the New Keynesian Phillips Curve, which posits a relationship between inflation and economic activity, with inflation expectations as a key determinant. He notes that much of the existing research is based on theoretical assumptions rather than robust empirical support. Supporting his claims, there is empirical evidence suggesting that inflation dynamics are better explained by lagged inflation and supply-side

factors rather than forward-looking expectations (Coibon and Gorodnichenko, 2015). Rudd (2021) also criticizes survey-based approaches to measuring inflation expectations simply stating that post 1970s high inflation period, inflation is no longer on workers' "radar screens" and does not drive workers' employment decisions.

If inflation expectations do not play as significant a role as previously thought, this could have major implications for monetary policy and management of inflation expectations. Therefore, the paper has contributed to a broader debate, specifically in relation to recent inflation dynamics, where supply chain issues, energy prices, and other factors have driven inflation rates higher post Covid. Rudd's paper combined with the relevance of inflation expectations during an inflation surge period, spurred a number of research efforts on inflation expectations.

Verbrugge and Zaman (2021) paper on US inflation expectations point out that consumer expectations have significant differences from professional forecasters and business expectations. They also show that consumer inflation expectations are a much worse predictor of actual inflation. Weber, Coibon and Gorodnichenko (2023) study household level data on US consumers to find a link between perceived and expected inflation challenging the link between consumer expectations and actual inflation. The researchers also indicate, that during the inflation surge, the heterogeneity of expectations also rises. Huber, Minina, Schmidt (2023) employ a RCT and establish a causal relationship between consumer inflation perceptions and expectations using data on German households. Since it is well documented that consumer inflation perceptions are highly heterogeneous and biased, this raises serious concerns about the relationship between inflation expectations and actual inflation. Bachmann, Berg and Sims (2015) study on US household readiness to spend indicate that higher inflation expectations had a negative effect on spending decisions in a near zero lower bound environment and had no effect otherwise. In other words, when operating at zero lower bound and increase in expected inflation results in lower aggregate demand exerting downward pressure on actual inflation. The authors indicated though that the results vary in accordance with the attributes of households. Those households whose inflation expectations were closer to actual ex-post inflation rate did operate more in line with economic theory and Euler's equation used in macroeconomic models.

On the other hand, a study on euro area household by Duca, Kenny and Reuter (2021) found some contrary results. The authors find a positive relationship between inflation expectations and household spending. What is more, the effect is found to be stronger when the interest rates are close to

zero. Duca et al. (2021) postulate that increase in inflation expectations can lead to substantial increases in aggregate consumption, especially when the lower bound on interest rates is binding. Country level data is consistent with the study on households; however, researchers indicate that there is a degree of heterogeneity among countries that could arise due to differences in economic structure and consumer behaviors. Rondinelli and Zizza (2020) research on Italian households indicate that the effect of inflation expectations might depend on the inflation level itself. The authors found that during a high inflation regime, consumers with higher inflation expectations are more likely to increase their current spending compared to future spending. This suggests that the main channel through which inflation expectations affect aggregate demand was dominated by intertemporal substitution effect. However, during a low inflation regime, households with higher inflation expectations had lower propensity to spend, indicating that income effect was the dominant mechanism. While the body of work on consumer inflation expectations is growing, there is still ambiguity on the effects of it to inflation.

Lastly, while some studies (Duca et al., 2021) focus on multi-country research, some studies focus on single country data. However, a question remains whether study of inflation expectations on multi-country data is beneficial as there is evidence in the academic literature emphasizing country differences in inflation as well as inflation expectations dynamics (Kucerova, Paksi and Konarik, 2024; Panagiotis and Argyrios, 2023; Szyszko and Rutkowska, 2019). Therefore, it is beneficial to test whether studying individual country data can produce considerably different results to a study in a panel data setting.

1.3. Recent Findings in Research of Inflation Expectations

While inflation expectations have been one of the fundamentals of modern macroeconomics for quite some time, yet the assumption of well-anchored, rational expectations among agents is increasingly challenged by empirical evidence. Recent period of elevated inflation levels and volatility has increased academic interest in understanding how expectations are shaped, how they respond to policy, and how they impact economic behavior. New findings in the field make use of several techniques, study subjects and modelling innovations. To better understand the results of these studies and present them in a coherent and systematic way, the discussion is divided into topics that best summarize the prevailing research directions: measurement innovation, randomized controlled trials, heterogeneity and formation of expectations, expectations of firms, and macroeconomic modelling advances.

1.3.1.Measurement Innovation

Several new measures complement existing ways of measuring inflation expectations. When it comes to consumer and household inflation expectations, European Commission's harmonized Business and Consumer Surveys has been complemented by the ECB Consumer Expectations Survey (CES) since 2020. It provides additional microdata and better consistency across countries (Gomes, Monteiro, and Ribeiro (2024); D'Acunto et al. (2024)). Another new survey has taken an indirect approach to measuring consumer inflation expectations. The survey is conducted by Morning Consult, a data intelligence company, and asks consumers to evaluate the change in income required to buy the same amounts of goods and services a year from the date of the survey. Survey is carried out weekly in US and monthly in 14 other countries. While it does measure individual and not aggregate consumption, such variations of the questions might be important in attempting to capture household expectations more accurately as several papers show that some households are poorly informed about the concept of inflation (Drager and Nghiem (2025); Hajdini et al. (2024); Kostyshyna and Petersen (2024)). Hajdini et al. (2024) show that aggregated individual inflation expectations follow closely the conventional survey techniques on aggregate inflations expectations as well as result in lower variance of ex-post forecast errors. Binder et al. (2024) make use of existing surveys to utilize the available high frequency data. Namely, while typical surveys (in their case Federal Reserve Bank of New York's Survey of Consumer Expectations (FRBNY SCE) are monthly, respondents are surveyed throughout the month, and the exact survey date is recorded. Comparing respondents with similar characteristics allows the use of their responses to be analyzed as event studies.

When it comes to firms, several new surveys have also been introduced. Namely, ECB's Survey on the Access to Finance of Enterprises (SAFE) included a pilot phase (from June 2023 to December 2023) and introduced (from January 2024) a quarterly survey with a module on euro area firms' inflation expectations (Baumann et al. (2024)). This expansion of the existing survey aims to provide consistent cross-country firm expectations with micro data available from respondents. A similar survey has been conducted in US since 2018 (Survey of Firms' Inflation Expectations (SoFIE)).

1.3.2. Randomized Controlled Trials

The emergence of new survey instruments has coincided with a broader shift in the literature on household and firm expectations toward greater use of randomized controlled trials (RCT) to assess how information treatments shape the formation of inflation expectations. Drager and Nghiem (2025) show that only around half of German consumers can correctly answer more than two out of five multiple choice questions about inflation and its' effects. What is more, only 20% of responders are aware of the inflation target of ECB is. The authors use both non-numeric information about inflation and monetary policy as well as quantitative information about inflation and central banks. The study determines that non-numeric information increases consumer literacy on inflation with the effect stronger for less informed households and remaining persistent for at least three months after the study. Also, the authors find that households receiving the treatment are more likely to provide quantitative inflation expectation responses. However, neither the literacy treatment, nor quantitative information treatment does not increase the accuracy of the inflation expectations. Such results are in contrast with the results obtained by Coibion et al. (2022). Though, a similar study by Drager, Lamla and Pfajfar (2024) on German households have determined that if the information treatment is about rising inflation, then the consumers raise both 12 months as well as longer horizon (5-10 years) inflation expectations. Such increase can be mitigated though. The authors determine that providing professional forecasts to consumers reduces the expected inflation across the whole term structure with the effects being smaller for longer horizon. This additional information also affects the household consumption and savings decisions. The authors caution though that as realized inflation later exceeded the communicated forecasts, the initial effects faded and then reversed (“information-reversal”): respondents placed negative weight on the earlier forecast and reverted toward priors and current inflation. Therefore, while CB communication can help temper increasing inflation expectations, biased forecasts can lead to exacerbation of spillover from surge of inflation to consumer expectations.

Kostyshyna and Petersen (2024) using RCTs studied what effects uncertainty of inflation might have on Canadian consumer expectations and spending. The authors aimed to find out how communication about the second moments of inflation would impact household expectations and their consumption decisions. Firstly, the authors had various information treatments – historic inflation information, Bank of Canada inflation target as well as their year-ahead inflation forecasts (with and without 95% confidence

interval) and professional forecasters year-ahead predictions (with and without the range of outlooks). The information treatment with the inflation forecast ranges acts as uncertainty measure for inflation. The authors find that all information interventions significantly reduce expected inflation with treatment effects ranging between 0.25 and 0.8 percentage points as well as decrease the variance among responses. Effects are stronger in the treatments related to forward looking information. Information treatment on the uncertainty of inflation, however, does not have any additional significant effects on neither the level nor the uncertainty about future inflation. The only noted effect of information on uncertainty was better anchoring compared to providing only point forecasts. Information on uncertainty was most impactful in reducing subjective uncertainty of expectations for individuals with high prior levels of subjective uncertainty. The authors conclude that simpler communication may be beneficial for households in retaining information. Kostyshyna and Petersen (2024) also study the effects on different demographic groups. They find that young people and those with lower level of education are more responsive to information treatments. Whereas age and education are significantly related to retention of information. The authors further study information treatment effects on consumer spending. They find that treated respondents increase their spending on both non-durable and durable goods in the upcoming three to six months after the survey. Treatments containing inflation uncertainty strengthen the effects on consumption. It is worthwhile noting that the data used in this research were collected before the inflation surge.

A similar study on the effects of inflation uncertainty with data after the peak of inflation in UK has been by Fischer, Schnattinger, and Herler (2025). The authors also have several information treatments, namely, they provide respondents with either average inflation forecasts of professionals, the difference between highest and lowest inflations forecasts of professionals (i.e. uncertainty) or both. The results of this research suggests that lower inflation uncertainty results in higher planned consumption of households with the strongest effect for non-hand-to-mouth and university-educated respondents. In a follow up survey, the authors find that actual consumption is indeed higher but not statistically significant. Fischer et al. also claim that lower inflation uncertainty increases respondent expected income (by a comparable amount to increase in planned spending) and reduces income uncertainty whereas the perceived risk of job loss remains unchanged. What is more, the study also finds that lower inflation uncertainty affects household portfolio composition with households shifting to a higher share of savings in

liquid assets with fixed returns. Authors explain this shift through better risk-return profile of these investments due to improved inflation outlook.

Grigoli and Sandri (2024) also employ RCTs to study household inflation expectations. Their study focuses on the effects that information about public debt influences US, UK, and Brazil consumer expectations. Researchers begin by asking about consumer beliefs on debt levels to find about the treatment shock where the information treatments are correct levels of respective country public debt. Then questions regarding credibility and anticipated actions of central bank as well as expectations about unemployment rate are asked. The authors find that on average respondents underestimate the level of public debt and the treatment induces respondents to revise inflation expectations upwards where the magnitude of the revision is proportional to the treatment shock (increase in public debt by 10 percent of GDP leads to an increase in one-year ahead inflation expectations by about 0.6 percent). Furthermore, credibility in central bank anchors inflation expectations, i.e. households who trust central banks more or are more knowledgeable about inflation target revise the expectations more modestly. However, households that increase their inflation expectations are not more likely to expect any action from central bank, implying that interpret high public debt levels as bad news for the economic outlook, leading to both higher inflation and unemployment expectations suggesting that consumers see high public debt as having stagflationary effects on the economy. This study also examines heterogeneity across respondents and finds that women on average increase inflation expectations twice as sharply after the treatment compared to men. Low-income households are also more sensitive with regards to inflation expectations when informed about the public debt levels.

New RCT research sheds a lot of light on how information can help manage and anchor household inflation expectations. It is especially useful in designing more impactful monetary policy communication. However, a lot of the studies highlight the heterogeneity in household responses – information treatment effects differ across multiple demographic and socioeconomic categories.

1.3.3. Heterogeneity and Formation of Expectations

Other studies not utilizing RCTs have also highlighted the heterogeneity of households alongside other issues. Gomes, Monteiro, & Ribeiro (2024) analyze EU consumer inflation expectations and perceptions from CES. Their findings confirm that on households have an upward bias in both perceptions and expectations of inflation relative to actual inflation. Also, their study

confirms heterogeneity between different households, especially with regards to age and income of respondents. Kliber, Szyszko, Prochniak, and Rutkowska (2023) find that neither consumers nor professionals forecast inflation accurately in Central and Eastern European countries with exchange rate fluctuations affecting forecast errors the most. Hajdini et al. (2024) using Morning Consult survey on indirect inflation expectations also find significant and nuanced heterogeneity between respondents. Firstly, the authors show that inflation expectations decrease with income. Secondly, younger respondents tend to have lower inflation expectations. However, while most of the countries in their analysis appear to have a monotonic relationship between age and inflation expectations, some do not. The authors provide China as an example, where the eldest cohort appears to have more similar expectations to the youngest cohort whereas middle-aged cohorts have higher inflation expectations. In terms of gender, Hajdini et al. (2024) also find varying results. While female respondents tend to report higher inflation expectations in US, Russia, Australia, and Canada, the opposite is found to be true in China, Germany, India, Italy, Japan, Mexico, South Korea, and Spain. Brazil, France, and the UK respondents appear to have no significant gender differences. This reinforces the argument that inflation expectations are context-dependent and shaped by local informational environments. What is more, they find that even more local experiences, namely, city level, have significant effects in inflation expectations formation.

Interestingly, Braggion, Meyerinck, Schaub, and Weber (2025) find supporting evidence about the importance of local experiences. Their study focuses on German households with the specific focus on differences between regions that have experienced more severe hyperinflation in 1920s. The authors document robust evidence of long-memory effects: historical hyperinflation continues to elevate expectations decades later through intergenerational and collective-memory channels.

Other studies also call for greater focus on formation of expectations. Dhamija, Nunes, and Tara (2025) study the effects of house prices in expectations formation for US consumers. They find that consumers overweight expected house price increases when forming inflation expectations. The most significant heterogeneity of respondents come from two factors – cognitive abilities and whether households moved house recently. Shahzad, Orsi, and Sharma (2024) find that past inflation, exchange rate, and energy shocks significantly contribute to household inflation expectations in the United States. Binder, Campbell, and Ryngaert (2024) study daily data on US household responses and find they are on average inattentive to FOMC monetary policy announcements and macroeconomic

data releases. Their results are mostly in line with previous research as well as research on EU households. However, the authors note that some announcements can affect inflation expectations. They argue this may reflect media-induced salience effects rather than direct learning. Also, since their study overlaps with Covid pandemic, the authors find that households responded significantly to news related to development of the pandemic (good news about vaccines would lower inflation expectations). Therefore, media saliency might also be of particular importance when forming inflation expectations. Stokman (2024) notes certain category salience in importance of euro area consumer inflation formation. Energy, food, transport and housing are indicated as particularly important categories for households. The results are in line with the previous literature focusing on the salience of certain categories of products and services. The author also finds that higher expected inflation raises consumption with the effect being the strongest when nominal interest rates are low – the results that are in line with the Euler equation but are contradictory to some of the findings from RCTs where sometimes higher inflation expectations trigger precautionary saving and reduction in consumption.

In contrast, Adams and Barrett (2024) use data from US and find that shocks to inflation expectations are deflationary and contractionary. Such results are inconsistent with the standard New Keynesian model. D’Acunto, Charalambakis, Georgarakos, Kenny, Meyer, and Weber (2024) provide a summary of the debate and recent findings in the literature. Authors agree with the findings that households often display deviation from rationality. Also, they state that households often act on their beliefs on future price developments. However, their actions are highly heterogeneous and context dependent. While ample evidence shows causal response of consumption to higher inflation expectations, this result is heterogeneous across population. It is driven by more educated, higher IQ and financially literate consumers. Moreover, the result is also context dependent as some studies suggest negative consumption response to higher inflation expectations especially in situations where increase in inflation would signal a drop in expected real income. The authors draw attention to a need in broader consumer sentiment research that could help explain the duality of the causal relationship between inflation expectations and consumption. Their findings also contribute to the debate of the importance and the effects of inflation expectations to actual inflation and the economy as a whole.

Overall, recent literature suggests high degree of heterogeneity not only in inflation expectations between different socio-economic and demographic factors but also in differences between countries or areas. What is more, there

still exists a problem in explaining the effects of higher inflation expectations on consumption. While it does appear that on average consumption of households increase as a response to increase in inflation expectations, other times it triggers a precautionary saving and reduction in consumption. While some households use simple heuristics – if economy is expected perform well, inflation expectations are lower and vice versa, others appear to have more nuanced understanding. The question remains regarding the aggregate effects, what are contexts or circumstances that could help better predict consumer response to higher inflation expectations.

1.3.4. Expectations of Firms

While expectations of firms have been studied in scientific literature, it has received much less attention than consumer or professional forecasters' expectations, partly due to more limited data from firms. The prevailing view has been that expectations of firms are less biased than household expectations but share some of the attributes. A few recent studies investigate firms' expectations in greater detail due to availability of new data from the beforementioned surveys. Baumann, Ferrando, Georgarakos, Gorodnichenko, and Reinelt (2024) study properties and causal effects of euro area firms. A lot of characteristics and attributes from household expectation research echo in their findings. Firstly, the authors find that there is significant heterogeneity in firm expectations depending on the firm and manager characteristics. Business environment of the firm also explains a lot of cross-sectional variation in beliefs. The study also shows that firms tend to extrapolate local conditions to aggregate conditions. Baumann et al. (2024) implement an RCT approach to studying the causal effects of inflation expectations. The treatments consist of information on past inflation and inflation forecasts. The results suggest that both treatments have significant effects on inflation expectations and are persistent for at least six months after the treatment, though forward-looking information treatments appear to have stronger effects. What is more, it directly translates into firms' plans related to pricing, wages, costs and employment suggesting how policy communications could influence macroeconomic conditions.

Candia, Coibion, and Gorodnichenko (2024) study firm expectations in US companies and reach somewhat similar conclusions. The data used in the study suggest that US firm managers are highly uninformed about monetary policy as well as inflation. While there are differences from household and professional forecasters' expectations, firms display a lot of characteristics associated with consumer expectations. Firstly, there is a high degree of

heterogeneity between firms that can partially be attributed to firm characteristics. Secondly, the authors find that heterogeneity persists not only in the short-term expectations, but into longer horizons as well (5 years) where expectations often differ from the Fed's inflation target suggesting low degree of anchoring. The authors also review a few studies that show causal relationship between firm beliefs and their investment and employment decisions. Therefore, while consumer inflation expectations are not a substitute for firms' beliefs, it appears that a lot of the issues identified in the studies of household expectations are also applicable to firms.

1.3.5. Macroeconomic Modelling Advances

Traditional macroeconomic models based on the full-information rational expectations hypothesis (FIRE) have seen criticism throughout the years. The recent research on modelling attempts to account for some of the stylized facts on empirical data of inflation expectations, namely persistent deviations, heterogeneity and salience of certain categories. It is done by introducing bounded rationality, limited attention, sticky information, heterogenous agents, and asymmetric information into the models. Dhamija et al. (2025) introduce a two-sector NK model and show that such model can provide better monetary policy implications compared to a model where households do not overweight house-price expectations.

Han (2024) presents a general equilibrium model that incorporates asymmetric information across households, firms, and central banks. This model allows reproduction of observed empirical patterns, such as households associating higher inflation with lower output growth (a stagflationary view), while professionals perceive inflation as a signal of stronger fundamentals. The model explains misaligned expectations by introducing heterogeneous signals (demand side via discount factor shocks and supply side via productivity shocks) and full information limitations on households, allowing each group to interpret macroeconomic shocks differently. These features have profound implications for business cycle dynamics and policy communication. The model results suggest that the equilibrium real wage decreases instead of increasing in response to a positive productivity shock when both sides meet in the labor market, a result that is consistent with the aggregate data observations.

Xie (2025) develops a Bayesian learning framework that captures how households update their beliefs about inflation in the presence of reporting errors and sampling noise. The model introduces heterogeneity in the speed of learning across households and shows that lower-educated agents exhibit

more sluggish adjustments to monetary policy changes. The findings suggest that central bank attempts to anchor inflation expectations may be less effective among socioeconomically disadvantaged populations. In a similar study, Jorgensen and Lansing (2025) first show that there has been a puzzle of missing disinflation and missing inflation observed during and after the Great Recession. The authors modify the New Keynesian Phillips Curve (NKPC) to allow for imperfectly anchored expectations and show that this imperfection reconciles the flattening of the Phillips curve and help explain the empirical puzzle. Dietrich (2024) attempts to tackle salience of consumer inflation expectations. His study first establishes that households overweight non-core components of inflation (especially energy) when forming inflation expectations. Then Dietrich (2024) argues for a sparsity-based bounded rationality framework to account for this pattern. He embeds this framework into a multi-sector NK model and shows that targeting headline rather than core inflation for central bank is beneficial as it results in higher welfare and better stabilizes the expectations that matter for demand.

These recent findings not only enhance our understanding of inflation expectation dynamics and formation but also offer practical guidance for policymakers aiming to stabilize expectations in an era of persistent uncertainty and volatile economic outlook. The reviewed literature shows that inflation expectations are formed through a complex interplay of information processing, cognitive biases, and exposure to salient shocks. However, important gaps remain. Firstly, reconciling theoretical responses to expectation shocks call for models that synthesize consumer sentiments, fiscal constraints and heterogeneous beliefs. Secondly, cross-country evidence shows that gender and age patterns differ internationally, cautioning against universal narratives. Third, the advancement in measurements of firm expectations call for models embedding this information into price and wage setting models.

1.3.6. Concluding Remarks

The analysis in Chapter 1 has laid the theoretical groundwork necessary for understanding the role of expectations. It has traced the evolution of the concept from its early roots in classical economics to its central place in contemporary models as well as outlined the measures used in estimating inflation expectations. The literature reviewed indicates a consensus on the significance of inflation expectations, yet it also reveals gaps in empirical validation, particularly concerning the accuracy of these expectations among different economic agents and the influence expectations have on

macroeconomic outcomes. Recognizing these challenges, the next chapter transitions from theoretical discussions to empirical investigation. In Chapter 2 the method for quantification of consumer inflation expectations is examined. It examines the methods available for converting qualitative survey data into quantitative measures, particularly, the Carlson-Parkin method and its adaptations. This methodological focus provides the analytical foundation for the empirical chapters that follow.

2. THE CARLSON-PARKIN QUANTIFICATION METHOD: ASSUMPTIONS AND EXTENSIONS

2.1. Consumer Survey Data

In the EU, The Joint Harmonised EU Programme of Business and Consumer Surveys has been launched since 1961 and has had been revised and conducted ever since. The European Commission conducts the survey on a monthly basis. In the survey, consumers are asked to evaluate both qualitative and quantitative perceptions and expectations of various questions regarding their households and state of the economy overall. Below is question 6 of the survey: *By comparison with what is happening now, do you think that in the next 12 months: (a) there will be a more rapid increase in prices; (b) prices will increase at the same rate; (c) prices will increase at a slower rate; (d) prices will stay about the same; (e) prices will fall slightly.*

Similar question is also asked about the perceived, i.e. the inflation consumers believe they have experienced in the past 12 months (question 5¹). Both of these questions have quantitative counterparts (questions 5.1² and 6.1³), however it is well documented that consumers' quantitative estimates of inflation are higher than official HICP inflation rate and are generally not reliable in measuring expectations (Arioli et al., 2017; Rutkowska and Szyszko, 2021). Therefore, questions of qualitative nature are preferred to their precise counterparts due to their greater reliability, higher response rates, and reduced cognitive burden on respondents. What is more, qualitative questions regarding inflation expectations also have a higher response rate allowing for a more comprehensive survey data (Pesaran and Weale, 2005). On the other hand, qualitative responses to the consumer surveys do not directly convey information on the magnitude of changes in the consumers' inflation perceptions and expectations, thus, quantification of qualitative responses is preferred. The simplest and the earliest attempt to quantifying the responses is called *balance statistic* (Anderson Jr, 1952) and is provided

¹ “How do you think that consumer prices have developed over the last 12 months? They have...: a) risen a lot b) risen moderately c) risen slightly d) stayed about the same e) fallen”

² „If question 5 was answered by 1, 2, 3 or 5: By how many per cent do you think that consumer prices have gone up/down over the past 12 months? (Please give a single figure estimate). Consumer prices have increased by X % / decreased by X %.

³ If question 6 was answered by 1, 2, 3 or 5: By how many per cent do you expect consumer prices to go up/down change in the next 12 months? (Please give a single figure estimate). Consumer prices will increase by X % / decrease by X %.

together with the consumer responses. Balance statistic is calculated as a difference between proportion of consumers that believe the prices will rise and the proportion of consumers that expect the inflation to fall. In a five category questionnaire the exact formula for calculating balance statistic is:

$$BS_t = A_t \times 1 + B_t \times 0.5 + C_t \times 0 + D_t \times (-0.5) + E_t \times (-1) \quad (1)$$

Where A_t , B_t , C_t , D_t , E_t denote proportion of people responding to the above-mentioned qualitative questions regarding consumer expectations (and perceptions) at time t .

Although balance statistics are straightforward and widely available, they conflate direction and magnitude of responses and impose arbitrary scoring weights. For this reason, more sophisticated approaches are needed. The other methods for quantifying responses to qualitative questions are probability approach, commonly referred to as Carlson-Parkin method and regression approach popularized by Pesaran.

2.2. Carlson-Parkin Method

The probability method was first proposed by Thiel (1952) and relied on the assumption that economic agents' expectations are based on the mean of their subjective probability distribution. If the mean is above a certain threshold level, respondents would report their expectation for the variable to go up and vice versa when the mean was below a certain level. If the mean of the respondent's probability distribution was within those two threshold levels, the respondent would believe that the variable in question will stay the same. This early formulation established the conceptual foundation for translating qualitative survey responses into implicit probability statements. However, the method only became popular in 1975 when Carlson and Parkin published their paper on quantifying qualitative response data. The authors presented a technique that utilized normal distribution for three category (trichotomous) data. The method assumed that all respondents had symmetric threshold parameters, i.e. ranges of imperceptibility, and these parameters stayed constant over time. Later, Batchelor and Orr (1988) adjusted the method to accommodate the current format of five response category (pentachotomous) data. Their extension enabled the use of modern EU consumer survey data, which employs five ordered qualitative response categories.

The method initially relied on utilising normal probability density function as distribution of responses. However, this assumption of the method was questioned even by Batchelor himself. He noted that inflation expectation

responses tend to be skewed and found empirical evidence that asymmetric or leptokurtic distributions could be more desirable (Batchelor, 1981). Distributional assumptions form the structural core of the Carlson–Parkin method, because the mapping from qualitative response categories to quantitative expectations depends directly on the assumed shape of respondents’ belief distribution. In heterogeneous populations, inflation perceptions are frequently asymmetric, clustered, or shaped by salient price changes, leading to empirical distributions that deviate from normality. Exploring alternative distributional forms is therefore essential, as they may align more closely with these behavioral patterns and yield more accurate quantification. Without evaluating such alternatives, it is impossible to determine whether the standard normality assumption imposes overly restrictive behavioral symmetry or inadvertently masks meaningful heterogeneity in the underlying data-generating process. An in-depth distributional analysis is thus necessary to ensure that the method’s foundational assumptions are compatible with observed characteristics of consumer expectations. Up to date, only a handful of researchers have measured impact of utilizing various distributions. Summary of their findings can be found in the Table 1.

It appears that initial research as well as statistical analysis indicated that normal distribution is not an ideal choice when quantifying qualitative responses. However, researchers have later found that use of alternative distributions provides little benefit in terms of accuracy of expectations. This has motivated the use of the normal distribution as a pragmatic default rather than a theoretically superior choice. In recent years, majority of the papers on inflation expectations only utilize the Carlson-Parkin method when quantifying consumer inflation expectations without questioning the distribution choice. It appears that the focus of the recent research is more on the macro-efficiency, forward-lookingness and rationality of the inflation expectations. Examples of such studies include research done by Kliber et al. (2023) where the authors test the determinants of inflation forecast errors in a select group of European countries (Albania, Czechia, Hungary, Poland, Romania, Serbia, Turkey). Inflation expectations unbiasedness and macro-efficiency is also tested. The study suggests that consumer inflation expectations do have systemic errors while the professional forecasters’ expectations are unbiased. However, macroeconomic efficiency is not met by both consumers and professional forecasters. Similar research was conducted by Rutkowska and Szyszko (2019). The authors investigate consumer expectations macro efficiency in Croatia, the Czech Republic, Hungary, Poland, and Romania. The results suggest that there is heterogeneity in the

macro efficiency and forward-lookingness of different countries. Research done by Szyszko et al. (2020) also looked into forward-lookingness of consumer inflation expectations and highlighted differences in countries. The authors find that the forecast errors are lower in the euro area than non-euro countries (excluding Sweden and UK). Researchers suggest that the difference arises due to the fact that euro area sample is based on developed countries while non-euro countries consist of transitional economies with more turbulent economic conditions. The degree of inflation expectations forward-lookingness are also lower in the latter countries.

Generally, all these papers have a few things in common. Firstly, they utilize the Carlson-Parkin method in its canonical form. The only methodological debate is on the scaling factor used when quantifying inflation expectations. The other common finding is the heterogeneity of inflation expectation dynamics between different countries. Nevertheless, there has been two relatively recent papers exploring the assumptions made in Carlson-Parkin method. The first paper was published by Lolic and Soric (2017). The main finding of the authors concludes that the choice of the distribution assumption when quantifying qualitative inflation expectations provide little benefit in forecasting accuracy. However, the researchers use euro area aggregate data. Therefore, in light of the studies highlighting the heterogeneity of inflation expectations, a question arises – do the same findings hold when considering individual country inflation expectations data.

The other paper by Rutkowska, Szyszko and Pietrzak (2023) focuses on finding the optimal method when quantifying consumer inflation expectations. One of the methods tested is the Carlson-Parkin method applied by utilizing various assumptions about the model including the choice of the distribution. The paper suggests three different evaluation criteria for the choice of the optimal method. Essentially, it is suggested that depending on what is the reference point of the accuracy – maximum covariance of balance statistics, direction of co-movement as well as balance statistics or minimization of forecast errors, there is an optimal choice of assumptions about the method used for individual countries. Although the optimal method is provided for individual countries in the results, there remains a question – what is the cost of choosing sub-optimal distribution when applying CP method. What is more, while 19 EU countries are tested in the paper, Baltic countries, namely, Lithuania, Latvia and Estonia are excluded from the research due to adoption of the Euro. The reason cited is that joining euro area might have affected the inflation expectation formation. Therefore, another question arises – did Euro adoption affect inflation expectations to have an impact on the optimal method choice. Baltic countries are also of particular

interest as these were the countries having one of the highest levels of inflation recently. Furthermore, inflation expectations of consumers are also greater and more volatile compared to western European countries or euro area as a whole. Therefore, this research aims to fill in the gap in the research and test whether the choice of distribution is important in the case of the Baltic countries as well as to measure the cost in accuracy of using normal distribution assumption.

Table 1. Literature on CP method employing non-normal distributions.

Author. Title of the study	Country of investigation	Findings
Batchelor and Orr (1988). <i>Inflation Expectations Revisited</i>	UK	Logistic distribution assumption method constitutes an upgrade form normal distribution (RMSE ratio 1.129)
Berk (1999). <i>Measuring Inflation Expectations: a Survey Data Approach</i>	Netherlands	Allowing for non-normal peakedness (central t dist.) and asymmetry (non-central t dist.) of the distribution did not increase the accuracy of the inflation prediction by the consumers (RMSE ratios 0.702-1.031)
Nielsen (2003). <i>Inflation Expectations in the EU - Results from Survey Data</i>	Aggregate data from EU countries (Belgium, The Netherlands, Luxembourg, France, Germany, Italy, Ireland, the United Kingdom, Denmark and Greece, from 1986 on Portugal and Spain, and since 1995 Finland, Sweden and Austria)	Both leptokurtic and asymmetric distributions do not improve the quality of inflation forecasting
Lyziak (2003). <i>Consumer Inflation Expectations in Poland</i>	Poland	Uniform distribution usage lead to less accurate consumer expectations when compared to normal distribution (RMSE ratio for the analyzed periods ranges from 0.786 to 0.913)
Lolic and Soric (2017). <i>A critical re-examination of the Carlson - Parkin method</i>	Euro area aggregate data	Several different models and distributions were tested. The research has found that in most models central t distribution

		provided the best results. However, researchers concluded that alternatives to normal distribution provide only marginal improvements in the accuracy of inflation expectations (RMSE ratios up to 1.056).
Rutkowska, Szyszko and Pietrzak (2023). <i>When all we have is not enough: a search for the optimal method of quantifying inflation expectations</i>	Austria, Belgium, Germany, Spain, Finland, France, Greece, Italy, Netherlands, Portugal, Bulgaria, Croatia, Czechia, Denmark, Hungary, Poland, Romania, Sweden and the UK	Normal, uniform, logistic, Student's t and skewed Student's t distributions are tested. Different procedures are found to be optimal for individual countries. No information on accuracy gains is provided in the paper.

2.3. Quantification of Qualitative Expectations

Having discussed the intuition behind the probability approach, the next step is to specify the foundational assumptions that make the CP method operational. Probability method foundation relies on three important cornerstones. As Nielsen (2003) summarized it, in order to utilize the CP method, the below assumptions are established:

1. Consumers inflation expectations are based on their individuals subjective probability density function;
2. Consumer individual probability density functions can be aggregated into a joint distribution $f(\boldsymbol{\pi}_{t+1}|\mathbf{F}_t)$;
3. Consumers' expectation formation process is based on two sensitivity intervals;

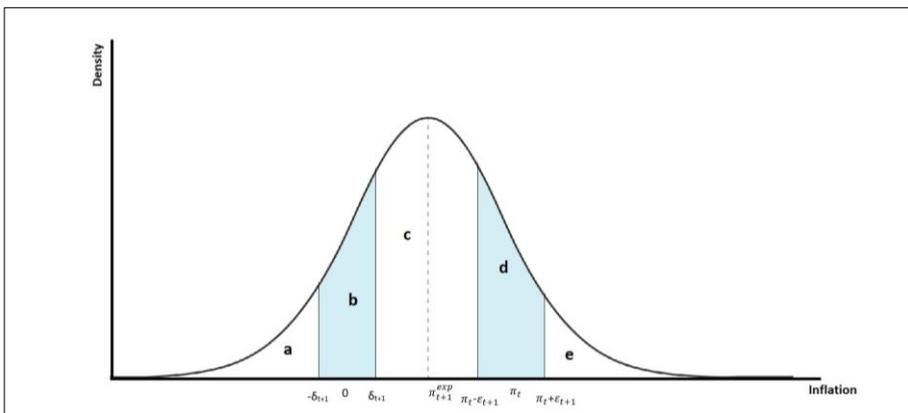
In practice, the application of the method relied on additional assumptions. These assumptions are not prerequisite of the quantification of qualitative responses, however, they simplify it. The first of those is *long term unbiasedness*, which implies that the average of consumer inflation expectations is equal to the average of actual inflation rate, i.e. average $\pi_{e,t+1}$ is equal to π_{t+1} . This assumption has been widely criticized, as consumers often exhibit systematic biases and persistent gaps relative to realized inflation. The second assumption concerns the sensitivity intervals (also referred to as ranges of imperceptibility). It is presumed that these intervals

are *symmetric*. The last assumption utilized is that the aggregate distribution of consumer responses is *normal*.

All of these assumptions have been challenged in the academic literature with varying results. Symmetry, normality, and unbiasedness remain strong simplifications that may distort quantified expectations in countries with volatile inflation dynamics or low financial literacy. In this research, part of the focus is on testing, whether alternative distributions are preferred, or normal distribution yields just as accurate results when quantifying consumer inflation expectations. In order to examine how qualitative expectations are quantified, a theoretical normal distribution is examined below. Firstly, the fraction of consumer responses is denoted as per below (Figure 1):

- Fraction of consumers who believe that *prices will fall slightly* lie in the interval $(-\infty; -\delta_t]$ (denoted as plot a);
- Interval $(-\delta_t; \delta_t]$ is a range of imperceptibility around 0, i.e. consumers that believe *prices will stay about the same* (denoted as plot b);
- $\pi_{e,t+1}$ is the mean expected inflation;
- Interval $(\delta_t; \pi_t - \epsilon_t]$ - *prices will increase at a slower rate* (denoted as plot c);
- π_t denotes *scaling parameter*, which usually is actual or perceived inflation at time t ;
- Interval $(\pi_t - \epsilon_t; \pi_t + \epsilon_t]$ is another range of imperceptibility denoting consumer response *prices will increase at the same rate* (denoted as plot d);
- The last interval, $(\pi_t + \epsilon_t; \infty)$, denotes response *there will be a more rapid increase in prices* (denoted as plot e).

Figure 1. Aggregate density function of inflation expectations, normal distribution.



The figure above assumes that the ranges of imperceptibility are symmetric (otherwise δ_t and ϵ_t would be split into two: δ_t^L, δ_t^U and $\epsilon_t^L, \epsilon_t^U$). Graphic aggregated probability distribution representation of the survey data allows expressing the CP quantification method mathematically. If we denote cumulative distribution function of aggregate probability density function of respondents as $F(\cdot)$, then we can write:

$$a = P(\pi_{e,t+1} \leq -\delta_t) = \int_{-\infty}^{-\delta_t} f(\pi_{e,t+1}) d\pi_{e,t+1} = F(-\delta_t) \quad (2)$$

$$b = P(-\delta_t < \pi_{e,t+1} \leq \delta_t) = \int_{-\delta_t}^{\delta_t} f(\pi_{e,t+1}) d\pi_{e,t+1} = F(\delta_t) - F(-\delta_t) \quad (3)$$

$$c = P(\delta_t < \pi_{e,t+1} \leq \pi_t - \epsilon_t) = \int_{\delta_t}^{\pi_t - \epsilon_t} f(\pi_{e,t+1}) d\pi_{e,t+1} = F(\pi_t - \epsilon_t) - F(\delta_t) \quad (4)$$

$$\begin{aligned} d &= P(\pi_t - \epsilon_t < \pi_{e,t+1} \leq \pi_t + \epsilon_t) = \int_{\pi_t - \epsilon_t}^{\pi_t + \epsilon_t} f(\pi_{e,t+1}) d\pi_{e,t+1} = \\ &= F(\pi_t + \epsilon_t) - F(\pi_t - \epsilon_t) \end{aligned} \quad (5)$$

$$e = P(\pi_t + \epsilon_t < \pi_{e,t+1}) = \int_{\pi_t + \epsilon_t}^{\infty} f(\pi_{e,t+1}) d\pi_{e,t+1} = 1 - F(\pi_t + \epsilon_t) \quad (6)$$

Using standardization we can rewrite the above equations to:

$$F^{-1}(a) = \frac{-\delta_t - \pi_{e,t+1}}{\sigma_{t+1}} = A_t \quad (7)$$

$$F^{-1}(a + b) = \frac{\delta_t - \pi_{e,t+1}}{\sigma_{t+1}} = B_t \quad (8)$$

$$F^{-1}(a + b + c) = \frac{\pi_t - \epsilon_t - \pi_{e,t+1}}{\sigma_{t+1}} = C_t \quad (9)$$

$$F^{-1}(a + b + c + d) = \frac{\pi_t + \epsilon_t - \pi_{e,t+1}}{\sigma_{t+1}} = D_t \quad (10)$$

$$a + b + c + d + e = 1 \quad (11)$$

Where σ_{t+1} denotes standard deviation of the expected inflation rate. The above equations allow expressing the unknown parameters in terms of respondent fractions and π_t , the scaling parameter. Rearranging equations 7-11 yields:

$$\pi_{e,t+1} = \pi_t \frac{A_t + B_t}{A_t + B_t - C_t - D_t} \quad (12)$$

$$\sigma_{t+1} = -2\pi_t \frac{1}{A_t + B_t - C_t - D_t} \quad (13)$$

$$\delta_t = \pi_t \frac{A_t - B_t}{A_t + B_t - C_t - D_t} \quad (14)$$

$$\epsilon_t = \pi_t \frac{C_t - D_t}{A_t + B_t - C_t - D_t} \quad (15)$$

Therefore, quantitative inflation expectations depend on the choice of the distribution function, $F()$, and scaling parameter, π_t . When the assumption about symmetric ranges of imperceptibility is not held then the quantification process is a bit more demanding and requires the use of ordered choice model framework (Lahiri, 2015) or CP approach with an asymmetric indifference interval (Claveria, 2006). Both approaches substantially increase computational complexity but improve flexibility in quantifying expectations.

2.4. Scaling Parameter

As discussed, the quantified inflation expectations depend on the choice of the scaling parameter, π_t . Academic literature mostly explores the use of either actual inflation rate or perceived inflation rate. The former is just the use of factual inflation rate and relies on the assumption that the respondents of the questionnaires are aware of the current inflation level. This assumption is often unrealistic, as survey evidence consistently shows that many consumers misperceive actual inflation, frequently overestimating it.. Some papers (eg. Nielsen, 2003) discuss the use of delayed actual inflation (i.e. π_{t-1}) due to the delay in the inflation statistics publication. This adjustment acknowledges the informational constraints faced by respondents when surveys are conducted before inflation figures for the reference month are released. What is more, average of multiple period factual inflation available to respondents can be also considered as an alternative. The use of perceived inflation as a scaling

parameter is the most common approach as it is less restrictive. The use of perceived inflation does not require hyper-awareness of the respondents and assumes that each respondent answers the survey having a perceived inflation in mind. The data on the perceived inflation rate can be obtained from the same consumer survey question 5 or 5.1. As question 5.1 is quantitative, it is easily available. However, it suffers from the criticism discussed in the previous sections. Notably, responses to Q5.1 tend to be heavily biased upward, display extreme values, and frequently diverge from HICP inflation, raising concerns about reliability.

What is more, the quantitative consumer responses on perceived inflation often remarkably differ from the actual inflation rate and, therefore, European Commission as well as many national partner institutions do not publish data on question 5.1. European commission provides quarterly aggregate data for euro area and euro zone, but data from individual countries is not public. Out of the other countries within scope of this research, only Lithuanian consumer responses to question 5.1 are publicly available. Question 5 is of qualitative nature and its use requires quantification procedure. When quantifying the perceived rate of inflation, however, a few challenges arise. Notably, qualitative question's answers regarding inflation perceptions are phrased a bit differently, than the question about expected inflation. Instead of response "increase at the same rate" (Q6), the respondents can choose "risen moderately" (Q5). In question 6, the response provides an anchor to consumer expectations, whereas question 5 only has one anchor point ("stayed about the same"). This is a problem because two anchor points are needed in a pentachotomous survey. Without two anchors, the intervals cannot be properly mapped to the underlying probability distribution. Therefore, one of the following solutions can be taken.

The first solution to quantifying expectations is to assume that the response in Q5 means the same as response in Q6 and just use the actual inflation rate from one year ago as a scaling parameter when quantifying qualitative perceptions (Lolic and Soric, 2017). However, use of this implies that consumers correctly perceive past inflation. It can be considered less restrictive as the use of actual inflation in quantifying price level expectations as consumers tend to adapt to previous levels of inflation.

Another solution to this issue is treating the question about price level perceptions as a trichotomous by combining "risen a lot", "risen moderately" and "risen slightly" into category that indicates that the prices went up (Millet, 2006, Nielsen, 2003). Although operationally convenient, this solution omits potentially valuable information on the intensity of perceived price increases and may flatten meaningful variation across respondents.

The last solution to quantification of consumer price level perceptions involves the definition of moderate inflation. Since the response indicates that the prices have "risen moderately", the anchor can be chosen as predefined moderate inflation. Researchers have suggested a few approaches to defining moderate inflation with the most popular ones being the average of inflation over the sample period (Millet, 2006, Nielsen, 2003), average of inflation from the beginning of the sample period to the time when the survey was conducted (Millet, 2006), central bank target chosen as the moderate inflation (Lolic and Soric, 2017, Lyziak, 2012), interpolation of moderate inflation based on actual inflation (Millet, 2006, Pop, 2016). The last method requires calculating what is the moderate inflation rate at the time of conducting the survey while employing some sort of linear or non-linear interpolation based on the selected sample of inflation data. This approach is appealing conceptually but more computationally intensive and somewhat arbitrary in specification.

Regardless of the chosen qualitative consumer price level perception quantification method, similar assumptions as in expectations quantification are generally taken. Namely, the ranges of imperceptibility are assumed to be symmetric and the distribution function of inflation perceptions also has to be assumed. What is more, Lyziak (2013) has shown that problems arise in cases when the chosen scaling parameter has non-positive values. In this research, I follow the truncated distribution approach suggested in his paper for scaling parameters with any negative values. This ensures mathematical consistency of the CP model under deflation or near-zero inflation conditions.

While the scaling parameter influences the magnitude of quantified expectations, it cannot correct distortions arising from an inappropriate distributional assumption. Because the distribution determines the structural shape of latent beliefs and the implied category thresholds, its validity must be established before any scaling can be meaningfully interpreted. Thus, distributional analysis represents a logically prior and methodologically more fundamental component of the CP framework.

3. CONSUMER INFLATION EXPECTATIONS QUANTIFICATION AND ACCURACY IN THE BALTIC COUNTRIES

In this chapter, I focus on distribution assumption of Carlson-Parkin (CP) method for quantifying consumer inflation expectations in the Baltic countries. While early literature on the CP method focused on investigating its assumptions, most of recent papers utilize some standard form of this method and analyze various aspects of consumer inflation expectations - accuracy, expectation formation determinants, rationality and forward-lookingness of agents, etc. (Kliber, Szyszko, Prochniak and Rutkowska, 2023; Rutkowska and Szyszko, 2022; Szyszko, Rutkowska and Kliber, 2020, etc.). The recent papers focusing on CP method itself by Lolic and Soric (2017) as well as Szyszko, Rutkowska, and Pietrzak (2023), however, have not addressed some worthwhile questions. While the former paper examines the accuracy of consumer inflation expectations when using non-normal probability distribution in CP method, it does so for aggregate Euro area data disregarding the heterogeneity of individual country inflation and consumer response dynamics. The latter research acknowledges the heterogeneity of inflation expectations but does not provide quantitative answers on the impact of a non-optimal distribution choice. What is more, their research does not include the Baltics countries in the data as these countries have adopted Euro currency during the sample studied. Therefore, the objective of this chapter is threefold.

Firstly, it aims to supplement the most recent papers on the use of different probability distributions in analyzing what the quantitative benefits are of choosing the optimal probability distribution instead of normal. Secondly, it fills the existing literature gap on the quantification of consumer inflation expectations in Baltic countries and investigates whether currency adoption had any significant impact on quantification of consumer expectations. Although the main focus is on the Baltic consumers, Polish and aggregate Euro area data are also analyzed, so as to maintain comparability with the other studies in the field. Thirdly, the forward-lookingness and predictive power of the Baltic consumer inflation expectations are tested.

3.1. Data Overview

The inflation and consumer response data used in this research are divided into several samples: full sample, from 2001 May to 2023 July, and four subsamples 1) from 2001 May to 2019 December, 2) from 2012 January to

2019 December, 3) from 2020 January to 2023 July and 4) subsamples for Baltic countries before and after adoption of the euro. The fourth subsample for Lithuania and Latvia consists of three years before and three years⁴ after the adoption of the euro, while for Estonia it is one year. Estonia was the first out of the three countries to adopt the euro in January 2011. Therefore, the subsample is limited to a year in order to limit the effect that the GFC might have had on consumer inflation expectations and quantification of them, as in 2009 the country experienced a period of deflation. It should be noted that the choice is arbitrary and does not eliminate the possibility that the results might still be affected.

Structure of the sample and the four subsamples follows directly from the inflation dynamics and consumer response patterns observed in the data. The full sample (2001.05–2023.07) spans both moderate and high inflation regimes, capturing the long-run distributional properties of expectations, including the skewness that becomes visible only over extended periods. The subsamples separating the pre-2020 period and the 2012–2019 moderate-inflation period allow assessing whether the CP method behaves differently under low-volatility conditions, as both the level and variance of inflation were markedly lower during this interval. The 2020–2023 subsample isolates the high-inflation surge, which is particularly useful given the substantially higher volatility in the Baltic states compared with the euro area. Finally, euro-adoption subsamples for Lithuania, Latvia, and Estonia are included because consumer response patterns shifted around the currency change. These subsamples jointly ensure that the robustness of CP assumptions is evaluated across distinct inflation environments and structural breaks.

I begin by analyzing the descriptive data on inflation in the countries analyzed. The main information can be found in Table 2. Considering the full sample analyzed, Latvia has had both the highest average and the most volatile 12-month inflation. In general, the Baltic countries had significantly higher average inflation than the euro area. In addition, the volatility of inflation is also much higher. Poland appears to have moderate average 12-month inflation and its volatility compared to the Baltic countries and the euro area. The subsample that excludes the recent period of high inflation tells a very similar story. The subsample consisting data from 2012 until 2020 can be considered the period of modest inflation. We can see that post GFC all the

⁴ shorter periods tested did not differ significantly in descriptive statistics. Three years ensure a sample that would be more robust in comparing the quantified inflation expectations results.

countries in consideration as well as euro area as a whole experienced significantly lower levels of inflation. It is notable that during this period inflation levels in Poland are comparable to those in the euro area, while the standard deviation of inflation is closer to the Baltic countries. Overall, not only the level of inflation but variance is substantially lower in this period as well. Therefore, it is particularly interesting comparing this subsample to others as it will indicate whether consumers inflation expectations are more accurate during the periods of lower inflation.

Mitchell and Zaman (2023) research on US consumers indicate otherwise. Their investigation on quantitative consumer inflation expectations concludes that expectations are more accurate during the periods of high inflation. Considering the the subsamples before and after euro adoption in the Baltic countries, the descriptive statistics cannot be compared between the countries as the periods are different. However, in the case of Lithuania, the data suggests that the pre euro adoption period appears to be similar to the post euro adoption in inflation dynamics. While in the case of Latvia, post euro adoption period had significantly lower inflation levels and standard deviation. Inflation in Estonia during the euro adoption period indicates that the inflation level was picking up. Before the euro, inflation appears to be lower in level, but markedly higher in the standard deviation. Nevertheless, such dynamics might be the results of the period analyzed (post GFC) and not the change of the currency.

Distinct dynamics in all the Baltic countries can lead to interesting insight on quantification of consumer inflation expectations as it can show whether inflation dynamics mattered in the choice of CP method assumptions. While there is no official rule when evaluating skewness of data, generally it is only notable when the values exceed -1 or 1. In the data analyzed this only the case in the full sample and the first subsample. This indicates that inflation subsample dynamics fall under symmetric distributions unless a long period sample is considered.

Data on quantitative consumer expectations (Q6.1) is only publicly available in the case of Lithuania (monthly) and euro area (quarterly), therefore will not be investigated in this research. Qualitative consumer responses are available and descriptive information about balance statistics is presented in the Table 3. Lithuanian consumers appear to be notably more pessimistic when evaluating the movement of future prices as the balance statistic of their responses is significantly higher in almost all the considered sample periods. What is more, the mean of the balance statistics varies little when comparing different subsamples, thus indicating that consumer responses do not correlate to the level of inflation as much as consumers in

other analyzed countries. When considering the full sample and the first subsample (2001.05-2019.12), Latvian and Estonian consumer response balance statistics have substantially higher means and standard deviations compared to aggregate euro area data.

However, there is a divergence in comparability when looking at the subsample from 2012 to 2020. In this subsample, Latvian consumer responses are comparable to those of euro area consumers while Estonian consumer responses remain substantially higher and more volatile to those of euro area consumers. This can partially be explained by slightly higher level of inflation in Estonia during this period. During the high inflation period balance statistics mean of Latvian and Estonian consumers are similar to euro area consumers, but the variance is notably higher. Meanwhile Polish consumer inflation expectation balance statistics appear to be most reactive to inflation levels, the mean of balance statistics was the lowest during the period of moderate inflation while it was the highest during the recent period of high inflation.

Considering the subsamples before and after euro adoption, both Lithuanian and Latvian share of consumers expecting inflation to increase was significantly higher before the currency change date. In the case of Estonia, the mean of balance statistics was comparable in both periods, but the variance of it was notably higher before the adoption of euro. It is of particular interest that not only mean of balance statistics, but the first quartile of all the subsamples and the countries analyzed is positive. It shows, that the share of consumers expecting the inflation level to increase is higher. This indicates that consumer qualitative responses might not follow a normal probability density distribution and have a negative skew as the share of consumers believing that the prices will deflate or remain the same is lower than the share believing the prices will rise at the same or more rapid pace. This suggests that there is indeed reason to try non-symmetrical distributions when applying CP method to consumer responses. While individual consumer response distribution is skewed, the data suggests that the balance statistic does not have many asymmetries as in all the subsamples the skewness coefficient is in the interval $[-1;1]$.

Overall, the Baltic states provide a particularly stringent environment for evaluating CP method. As shown by the descriptive evidence, inflation dynamics in Lithuania, Latvia, and Estonia have been markedly different from those observed in the euro area, with substantially higher average inflation and considerably greater volatility across most sample periods. Consumer response patterns also display notable differences: balance statistics in the Baltic countries are more variable and, in the case of Lithuania, consistently

more pessimistic than in the euro area, indicating a weaker alignment between realized inflation and consumer perceptions. These features suggest that households in the region may form expectations under more volatile and asymmetric conditions, increasing the likelihood that the underlying distribution of expectations deviates from the symmetry typically assumed in the CP framework. Moreover, structural shifts such as euro adoption introduced clear changes in consumer response dynamics even when inflation behavior itself remained relatively stable, particularly in Lithuania. Taken together, these characteristics imply that the Baltic countries are not merely under-researched, but represent a demanding context in which the robustness of alternative distributional assumptions and scaling choices can be meaningfully assessed.

Visual representation of inflation together with balance statistics in analyzed countries as well as euro area is provided in Figures 2-6. The euro area graph suggests that consumer responses follow current levels of inflation, i.e. if the inflation level is high, consumers expect prices in 12 months to rise faster than they are currently rising and, equivalently, during periods of low inflation, the fraction of consumers expecting lower levels of inflation to persist increases. Similar situation can be observed in the analyzed individual country graphs. Assuming that consumers are forward looking, one would expect the balance statistic to lead actual inflation. Since this pattern is not evident in the data, it is necessary to establish, first, whether consumer responses exhibit forward-looking behavior and, second, if they do, which expectation horizon aligns most closely with realized 12-month inflation. To examine this, cross-correlations between year-on-year inflation and the balance statistics are computed, with the results presented in Table 4.

Table 2. Descriptive statistics of YoY inflation. Source: Author's calculations.

	LT	LV	EE	PL	EA
Mean (2001.05-2023.07)	3.43%	4.22%	4.07%	2.99%	2.07%
Std. Deviation (2001.05-2023.07)	4.38	4.88	4.32	3.18	1.84
Median (2001.05-2023.07)	2.51%	2.93%	3.66%	2.34%	1.91%
Quartile 1 (2001.05-2023.07)	0.53%	0.85%	1.36%	1.07%	1.05%
Quartile 3 (2001.05-2023.07)	4.12%	6.41%	4.76%	3.94%	2.41%
Skewness (2001.05-2023.07)	1.93	1.42	1.92	2.07	2.07
Mean (2001.05-2019.12)	2.49%	3.60%	3.33%	2.05%	1.68%
Std. Deviation (2001.05-2019.12)	2.78	3.89	2.57	1.63	0.93
Median (2001.05-2019.12)	2.37%	2.89%	3.55%	1.79%	1.89%
Quartile 1 (2001.05-2019.12)	0.49%	0.92%	1.43%	0.86%	1.09%
Quartile 3 (2001.05-2019.12)	3.48%	5.93%	4.44%	3.55%	2.29%
Skewness (2001.05-2019.12)	1.28	1.23	0.74	0.13	-0.35
Mean (2012.01-2019.12)	1.61%	1.42%	2.23%	1.06%	1.14%
Std. Deviation (2012.01-2019.12)	1.49	1.30	1.57	1.38	0.82
Median (2012.01-2019.12)	1.73%	1.55%	2.56%	0.90%	1.22%
Quartile 1 (2012.01-2019.12)	0.36%	0.27%	0.54%	-0.20%	0.46%
Quartile 3 (2012.01-2019.12)	2.81%	2.68%	3.60%	1.79%	1.71%
Skewness (2012.01-2019.12)	-0.06	-0.06	-0.24	0.56	0.08
Mean (2020.01-2023.07)	8.30%	7.46%	7.95%	7.95%	4.10%
Std. Deviation (2020.01-2023.07)	7.17	7.61	8.04	4.50	3.44
Median (2020.01-2023.07)	6.92%	5.79%	6.18%	6.20%	3.97%
Quartile 1 (2020.01-2023.07)	1.37%	0.19%	0.72%	3.73%	0.92%
Quartile 3 (2020.01-2023.07)	14.90%	14.73%	15.32%	12.57%	7.18%
Skewness (2020.01-2023.07)	0.35	0.49	0.35	0.45	0.20
Mean (pre euro adoption)	1.51%	2.14%	2.69%	-	-
Std. Deviation (pre euro adoption)	1.31	1.78	1.92	-	-
Median (pre euro adoption)	0.97%	2.00%	2.75%	-	-
Quartile 1 (pre euro adoption)	0.35%	0.32%	2.19%	-	-
Quartile 3 (pre euro adoption)	2.82%	3.84%	3.89%	-	-
Skewness (pre euro adoption)	0.37	-0.09	-0.62	-	-
Mean (post euro adoption)	1.21%	0.33%	4.96%	-	-
Std. Deviation (post euro adoption)	1.91	0.66	0.45	-	-
Median (post euro adoption)	0.64%	0.43%	5.05%	-	-
Quartile 1 (post euro adoption)	-0.23%	-0.15%	4.76%	-	-
Quartile 3 (post euro adoption)	3.13%	0.76%	5.29%	-	-
Skewness (post euro adoption)	0.43	0.19	-0.88	-	-

Table 3. Descriptive statistics of Balance statistics of consumer inflation expectations.
Source: Author's calculations.

	LT	LV	EE	PL	EA
Mean (2001.05-2023.07)	42.66	27.65	32.54	28.05	19.25
Std. Deviation (2001.05-2023.07)	14.57	20.58	21.72	14.59	10.79
Median (2001.05-2023.07)	44.72	25.71	36.50	27.90	18.84
Quartile 1 (2001.05-2023.07)	33.06	16.35	18.91	19.80	11.80
Quartile 3 (2001.05-2023.07)	53.01	43.65	47.52	38.15	26.17
Skewness (2001.05-2023.07)	-0.50	-0.51	-0.42	-0.06	0.28
Mean (2001.05-2019.12)	43.25	27.31	33.05	24.98	17.82
Std. Deviation (2001.05-2019.12)	14.72	21.21	21.95	13.01	9.78
Median (2001.05-2019.12)	45.98	25.72	37.44	25.80	18.49
Quartile 1 (2001.05-2019.12)	32.98	16.58	20.29	17.04	11.14
Quartile 3 (2001.05-2019.12)	53.66	44.21	46.78	35.01	24.99
Skewness (2001.05-2019.12)	-0.49	-0.58	-0.47	-0.23	-0.14
Mean (2012.01-2019.12)	39.87	19.32	26.93	15.77	16.96
Std. Deviation (2012.01-2019.12)	10.18	10.16	17.78	11.56	7.81
Median (2012.01-2019.12)	40.19	18.73	23.72	16.80	18.84
Quartile 1 (2012.01-2019.12)	32.78	11.80	14.46	5.76	9.58
Quartile 3 (2012.01-2019.12)	48.56	25.98	42.28	23.44	22.05
Skewness (2012.01-2019.12)	-0.30	0.17	0.06	0.09	-0.14
Mean (2020.01-2023.07)	39.58	29.44	29.92	44.06	26.70
Std. Deviation (2020.01-2023.07)	13.50	17.04	20.54	11.69	12.75
Median (2020.01-2023.07)	42.68	23.38	33.10	47.05	24.07
Quartile 1 (2020.01-2023.07)	33.58	15.58	13.88	37.15	16.89
Quartile 3 (2020.01-2023.07)	49.28	43.30	50.60	51.73	36.44
Skewness (2020.01-2023.07)	-0.79	0.39	-0.17	-0.55	0.49
Mean (pre euro adoption)	50.14	30.17	26.33	-	-
Std. Deviation (pre euro adoption)	3.50	8.38	17.65	-	-
Median (pre euro adoption)	49.89	30.77	33.29	-	-
Quartile 1 (pre euro adoption)	47.76	23.94	12.03	-	-
Quartile 3 (pre euro adoption)	53.00	35.93	40.88	-	-
Skewness (pre euro adoption)	0.21	0.02	-0.46	-	-
Mean (post euro adoption)	29.54	10.28	25.42	-	-
Std. Deviation (post euro adoption)	6.18	7.13	4.49	-	-
Median (post euro adoption)	28.74	8.32	24.75	-	-
Quartile 1 (post euro adoption)	26.27	5.83	22.99	-	-
Quartile 3 (post euro adoption)	34.00	15.75	27.43	-	-
Skewness (post euro adoption)	-0.27	0.89	0.30	-	-

Figure 2. Lithuania YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.

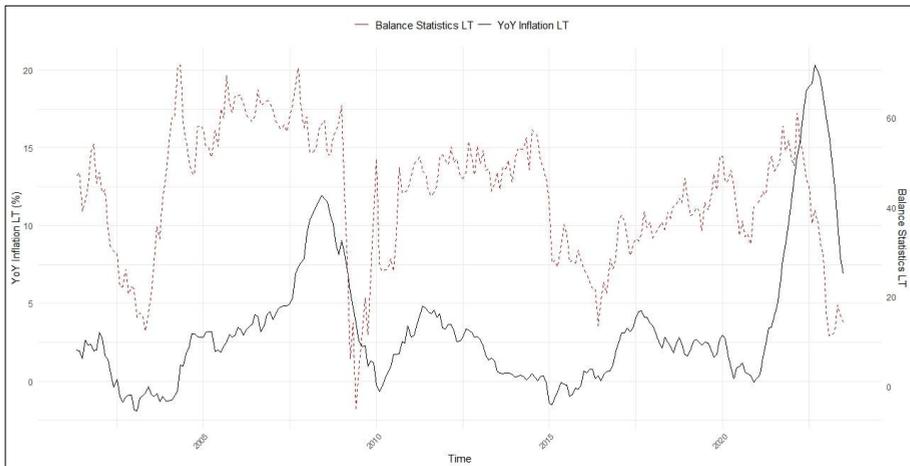


Figure 3. Latvia YoY inflation (left axis) and consumer balance statistics (right axis). Source: Eurostat, ec.europa.eu.

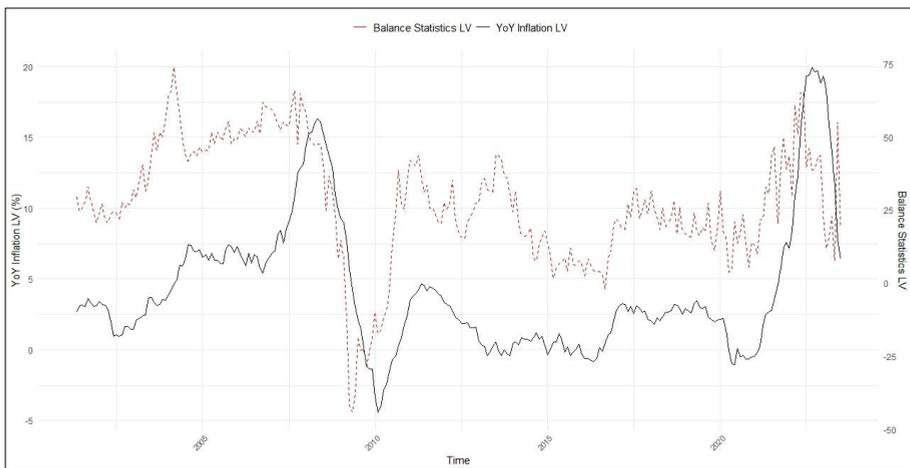


Figure 4. Estonia YoY inflation (left axis) and consumer balance statistics (right axis).
Source: Eurostat, ec.europa.eu.

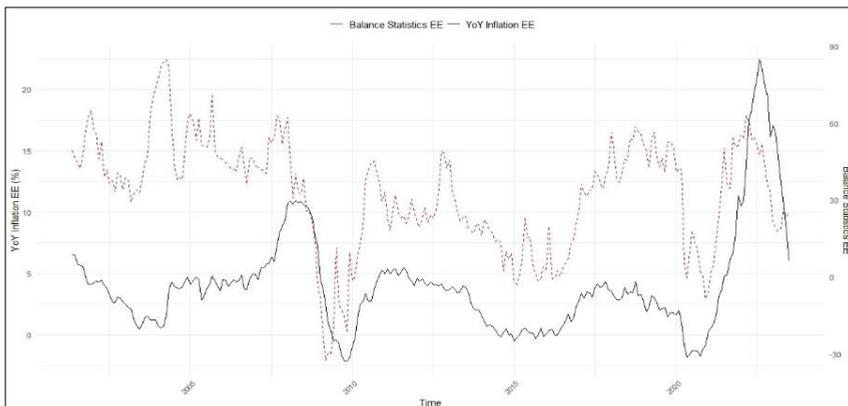


Figure 5. Poland YoY inflation (left axis) and consumer balance statistics (right axis).
Source: Eurostat, ec.europa.eu.

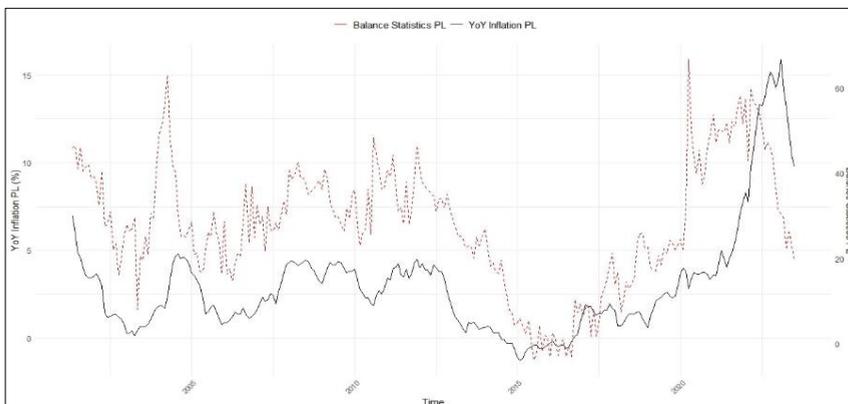


Figure 6. Euro area YoY inflation (left axis) and consumer balance statistics (right axis).
Source: Eurostat, ec.europa.eu.

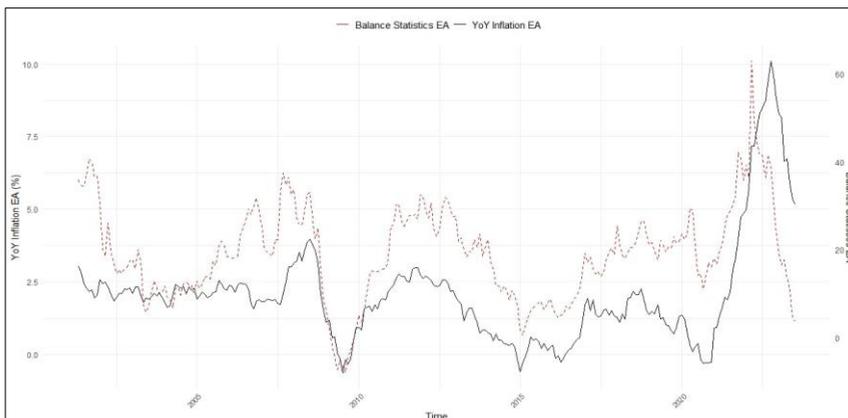


Table 4. Cross correlation between YoY inflation and balance statistics. Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Corr(π_t, BS_t)	0.141	0.505	0.364	0.570	0.578
Corr(π_{t+12}, BS_t)	0.298	0.576	0.180	0.608	0.370
Highest corr with BS_t	$\pi_{t+8}, 0.379$	$\pi_{t+6}, 0.695$	$\pi_{t+5}, 0.445$	$\pi_{t+7}, 0.684$	$\pi_{t+4}, 0.644$
Sample 2001.05-2019.12					
Corr(π_t, BS_t)	0.417	0.566	0.407	0.732	0.709
Corr(π_{t+12}, BS_t)	0.371	0.677	0.351	0.437	0.129
Highest corr with BS_t	$\pi_{t+6}, 0.509$	$\pi_{t+7}, 0.761$	$\pi_{t+6}, 0.541$	$\pi_{t+2}, 0.744$	$\pi_t, 0.709$
Sample 2012.01-2019.12					
Corr(π_t, BS_t)	0.177	0.242	0.680	0.773	0.887
Corr(π_{t+12}, BS_t)	-0.690	-0.071	0.214	-0.032	0.213
Highest corr with BS_t	$\pi_{t-20}, 0.701$	$\pi_{t-12}, 0.420$	$\pi_{t-6}, 0.712$	$\pi_t, 0.773$	$\pi_t, 0.887$
Sample 2020.01-2023.07					
Corr(π_t, BS_t)	-0.160	0.511	0.644	-0.220	0.458
Corr(π_{t+12}, BS_t)	0.485	0.558	0.343	0.587	0.469
Highest corr with BS_t	$\pi_{t+9}, 0.654$	$\pi_{t+3}, 0.758$	$\pi_{t+3}, 0.743$	$\pi_{t+11}, 0.607$	$\pi_{t+5}, 0.798$
Sample pre euro adoption					
Corr(π_t, BS_t)	-0.059	-0.171	-	-	-
Corr(π_{t+12}, BS_t)	0.314	0.691	-	-	-
Highest corr with BS_t	$\pi_{t+12}, 0.314$	$\pi_{t+11}, 0.729$	-	-	-
Sample post euro adoption					
Corr(π_t, BS_t)	0.434	0.366	-	-	-
Corr(π_{t+12}, BS_t)	-0.657	0.094	-	-	-
Highest corr with BS_t	$\pi_{t-1}, 0.548$	$\pi_{t-1}, 0.534$	-	-	-

The cross-correlation results indicate that in the full sample consumer response balance statistics are more correlated with current levels of inflation in Estonia and euro area. Whereas the balance statistics are more correlated with YoY inflation in 12 months time in Lithuania, Latvia and Poland, although the difference in correlations is not large. It is noteworthy, that the lowest correlation is in the case of Lithuania consumer responses. The result coincides with the findings of Claveria (2016), who shows that Lithuanian consumers were among the least able to anticipate YoY GDP growth in Central and Eastern Europe when quantifying survey responses.

When inspecting cross correlation in the sample from May 2001 to December 2019, the correlation between balance statistics and current YoY inflation is higher in every analyzed country as well as euro area than in the full sample. Correlation between balance statistics in period t and $t+12$ inflation is higher in Lithuania, Latvia, and Estonia. However, it is lower in the case of Poland and euro area as a whole.

Interesting results are found when inspecting the sample from 2012 to 2020. In the case of the Baltic countries, the highest correlation is observed with the past inflation, whereas Polish and euro area consumer responses correlate the most with current level of inflation. This may suggest a degree of backward-lookingness of consumers in the Baltics during times of moderate inflation. Another reason for such results might be related to the adoption of the euro during this period. Correlation before the euro adoption suggests that consumers were significantly more forward-looking in Lithuania and Latvia. In the case of Estonia, the sample size is too short to infer any conclusions, therefore correlations are not provided. Although correlation may be a useful indicator about the time horizon considered when responding to the questionnaire, it is by no means a definite proof. Therefore, it should be investigated further when the qualitative response data is quantified.

3.2. Quantification of Inflation Expectations

This section begins by presenting the quantified consumer inflation expectations. Consumer responses are quantified using the samples considered above. The quantification procedure is performed using 5 different assumptions about the survey response distributions: normal, logistic, central t , and two different non-central t distributions. In the case of non-central t distributions, a non-centrality parameter needs to be provided. Nielsen (2003) argues that it cannot be determined within the system, as the distribution function is assumed to be given. In this study, I postulate that consumer response balance statistics follow either an autoregressive (AR) or a random

walk (RW) process. If it is an AR process, unconditional expectations can be found. This could define the non-centrality parameter used. If it is a random walk process, then its unconditional expectation is a constant and it could also be used as a non-centrality parameter. Since the exact unconditional expectation cannot be found in the case of RW, the sample mean is used as a proxy for it. To support such assumptions, Augmented Dickey Fuller and Phillips-Perron test results for unit roots are presented in Table 5. The tests confirm that at 5% the significance level a unit root is present in all the periods considered. With the 10% significance level, Estonian consumer response balance statistics do not have a unit root per both ADF and PP tests in the full sample, but a unit root is present when considering subsamples. Therefore, the mean of the sample divided by 100 is used as the first non-centrality parameter. Since the parameter is a constant, it should shift the expected inflation values downwards. The second non-centrality parameter used was proposed by Berk (1999). It is constructed as the difference between latest official YoY inflation rate and the average YoY inflation rates in the previous 12 months. This definition makes the non-centrality parameter responsive to recent inflation dynamics, capturing short-run deviations from medium-term inflation trends.

Four different scaling parameters have been adopted in the quantification procedure, namely, the actual YoY inflation rate (π_t), the delayed actual inflation rate (π_{t-1}) and two perceived inflation rates using qualitative consumer responses. Perceived inflation rate is quantified assuming that the response categories in consumer questionnaire questions 5 and 6 are the same.

The first perceived inflation rate uses the actual YoY inflation rate from 12 months ago (π_{t-12}). The second perceived inflation rate is calculated by defining moderate inflation rate as the average of inflation from the beginning of the sample period to the time when the survey was conducted. Graphical representations of quantified consumer inflation expectations are provided in the Figures 7-11 where the scaling parameter used was actual inflation. Annex A contains graphical representations for other scaling parameters. Root mean squared errors of using each of the scaling parameters are also provided in Annex A Tables 23-26. Forecast error is calculated as actual YoY year ahead inflation (π_{t+12}) minus quantified consumer expected inflation rate ($\pi_{e,t}$). Although widely used, this measure implicitly assumes expectation unbiasedness (Rutkowska et al., 2022). Thus, RMSE should be interpreted as an empirical accuracy metric rather than as a normative measure of expectation rationality.

Table 5. Augmented Dickey-Fuller and Phillips-Perron test results. Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Augmented Dickey-Fuller	-1.23	-1.51	-1.81	-1.49	-1.82
<i>p-value</i>	0.238	0.139	0.071	0.147	0.070
Phillips-Perron	-2.55	-5.58	-6.25	-3.69	-5.44
<i>p-value</i>	0.360	0.110	0.088	0.266	0.122
Sample 2001.05-2019.12					
Augmented Dickey-Fuller	-0.850	-1.37	-1.35	-1.51	-1.58
<i>p-value</i>	0.375	0.189	0.197	0.139	0.112
Phillips-Perron	-1.66	-3.86	-4.08	-3.70	-4.06
<i>p-value</i>	0.434	0.251	0.233	0.264	0.234
Sample 2012.01-2019.12					
Augmented Dickey-Fuller	-0.367	-1.130	-0.215	-1.660	-1.049
<i>p-value</i>	0.538	0.274	0.581	0.093	0.302
Phillips-Perron	-0.324	-2.270	-0.453	-2.710	-1.530
<i>p-value</i>	0.617	0.380	0.588	0.343	0.442
Sample 2020.01-2023.07					
Augmented Dickey-Fuller	-1.080	-0.686	-1.169	-0.462	-0.803
<i>p-value</i>	0.287	0.256	0.581	0.506	0.386
Phillips-Perron	-0.981	-2.790	-1.890	-0.430	-1.050
<i>p-value</i>	0.487	0.330	0.408	0.589	0.481

Figure 7. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.

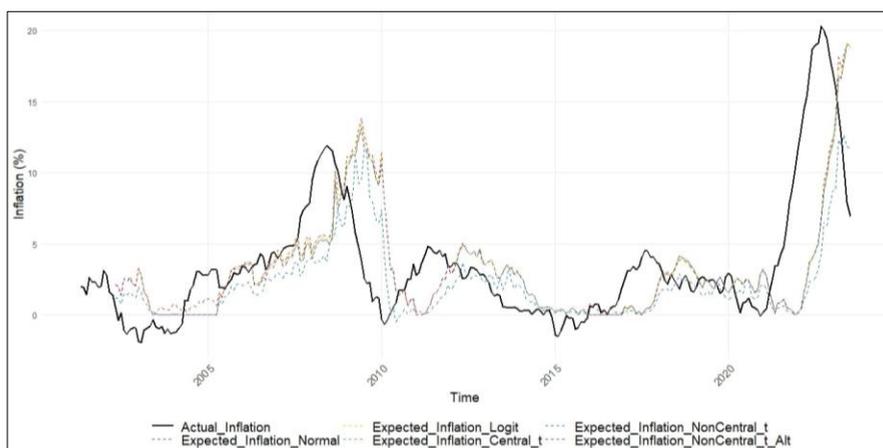


Figure 8. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.

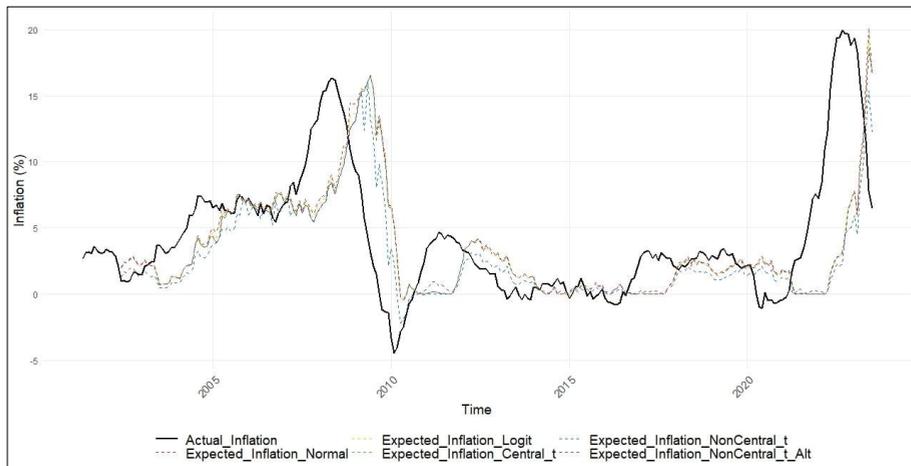


Figure 9. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.

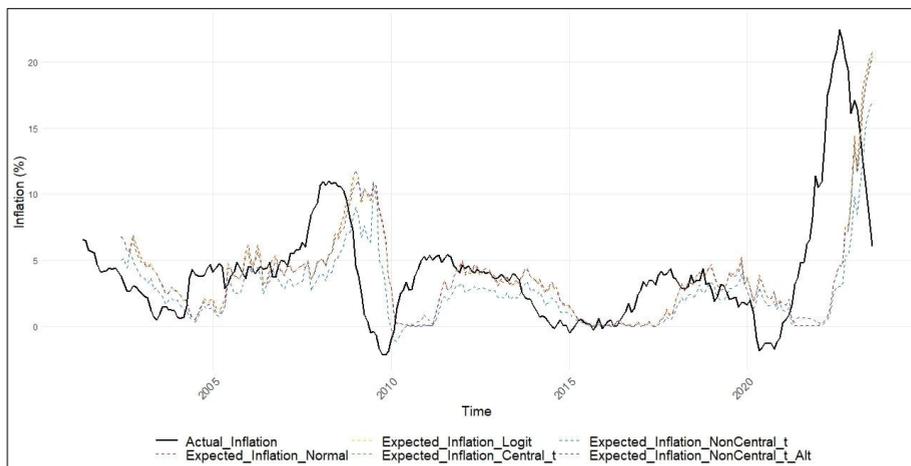


Figure 10. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.

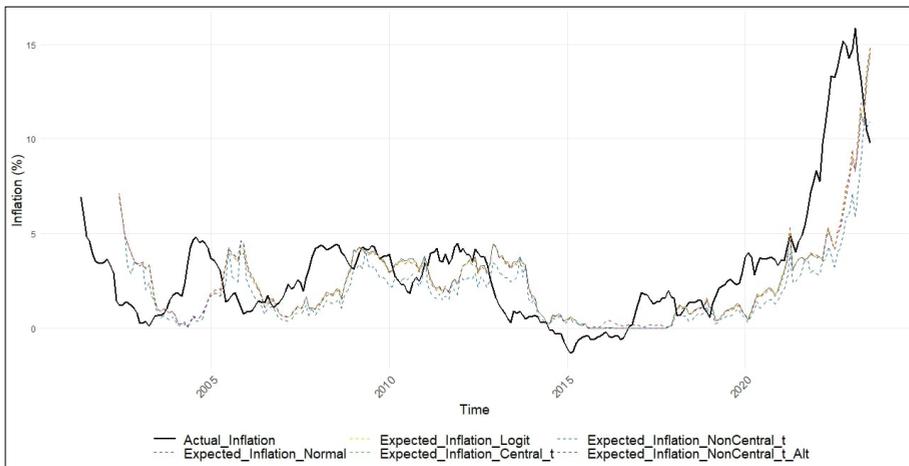
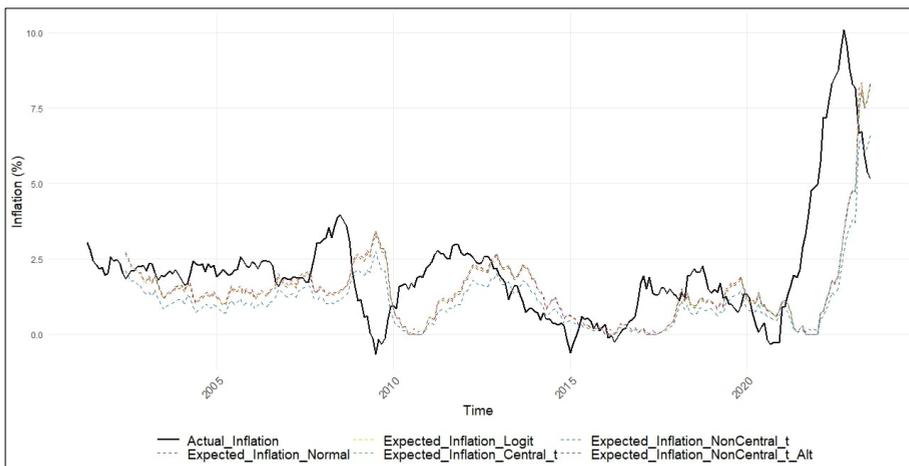


Figure 11. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using actual YoY inflation (π_t) as a scaling parameter.



RMSE values in the tables are noticeably larger for the Baltic countries compared to Poland and the aggregate euro area in most of the samples analyzed. This means that the resulting consumer inflation expectations have greater deviation from actual inflation in 12 months time and can be considered less accurate in Baltic countries. Such results could stem from either different inflation dynamics in the Baltics or less precise consumer expectations. I attribute higher RMSE values in the Baltic countries to higher inflation volatility in the region as the consumer response statistics of Table 3 suggest notable differences in the dynamics of consumer responses in different Baltic countries. Also, in the subsample from 2012 to 2020, the inflation variance in Poland is closer to the Baltic countries and the RMSE values are similar as well. The RMSE values do not differ much when choosing an alternative to normal distribution assumption with a few notable exceptions. Both, the low variation in the RMSE values and the graphical representation of the consumer expectations suggest that alternative distribution assumptions alter the expected inflation rate only slightly. Nevertheless, a more detailed comparison of alternative distribution assumptions is done by contrasting the results of the normal distribution assumption to the alternatives discussed in the beginning of this subsection.

With regards to the scaling parameters used, full sample consumer expectations were the most accurate using lagged actual YoY inflation (π_{t-1}) as scaling parameter for all countries and euro area as a whole. However, the differences between π_t and π_{t-1} are negligible. Such results mostly hold in the subsamples as well. The only exception is the moderate inflation sample period (from 2012 to 2020) where the use of running average inflation as scaling parameter for perception of inflation was preferred in the case of euro area consumers and yielded noticeably lower RMSE values. Such results are hardly surprising as the use of actual YoY inflation (or lagged YoY inflation) as a scaling parameter assumes that the consumers are aware of the current inflation rate and should provide best results in terms of expectation accuracy.

Since one of the main focus areas of this research is on the use of alternative distributions to normal, below presented are Tables 6 to 9 comparing RMSE ratios of normal distribution assumption to indicated alternative distributions. The highest value of the ratio is indicated in bold, unless the ratio is lower than 1, which means that the use of normal distribution assumption provided the most accurate results.

Table 6. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using actual YoY inflation (π_t) as a scaling parameter. Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample					
Logistic	0.997	0.992	0.994	0.992	0.999
Central t	0.997	0.987	0.993	0.983	1.002
Non-central t	0.999	1.031	1.002	0.898	0.948
Non-central t	0.996	0.987	0.993	0.982	1.001
Sample					
Logistic	0.996	0.983	0.990	0.993	1.001
Central t	1.000	0.972	0.985	0.986	1.004
Non-central t	1.064	1.040	1.041	0.998	0.989
Non-central t	0.999	0.970	0.984	0.986	1.004
Sample					
Logistic	0.998	0.977	1.004	0.988	0.994
Central t	1.001	0.971	1.007	0.976	0.991
Non-central t	1.115	1.035	1.045	1.022	0.999
Non-central t	1.001	0.972	1.007	0.975	0.990
Sample					
Logistic	0.997	1.000	0.995	0.990	0.998
Central t	0.994	1.002	0.998	0.981	1.001
Non-central t	0.949	0.975	0.973	0.761	0.925
Non-central t	0.994	1.003	0.998	0.981	1.001
Sample pre					
Logistic	1.014	0.925	0.946	-	-
Central t	1.028	0.919	0.946	-	-
Non-central t	1.623	0.998	0.955	-	-
Non-central t	1.028	0.921	0.947	-	-
Sample post					
Logistic	0.991	0.974	0.962	-	-
Central t	0.995	0.969	0.963	-	-
Non-central t	0.967	1.003	0.879	-	-
Non-central t	0.994	0.969	0.964	-	-

Table 7. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using 1 period lagged actual YoY inflation (π_{t-1}) as a scaling parameter. Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Logistic	0.995	0.987	0.989	0.989	0.997
Central t	0.994	0.979	0.986	0.978	0.999
Non-central t	0.986	1.021	0.982	0.887	0.939
Non-central t 2	0.993	0.978	0.985	0.977	0.998
Sample 2001.05-2019.12					
Logistic	0.995	0.978	0.986	0.991	1.001
Central t	0.998	0.964	0.979	0.981	1.005
Non-central t	1.068	1.040	1.035	0.994	0.988
Non-central t 2	0.997	0.961	0.977	0.980	1.004
Sample 2012.01-2019.12					
Logistic	0.997	0.977	1.004	0.986	0.994
Central t	0.999	0.971	1.007	0.971	0.992
Non-central t	1.116	1.029	1.040	1.012	0.991
Non-central t 2	1.000	0.972	1.007	0.970	0.991
Sample 2020.01-2023.07					
Logistic	0.996	0.995	0.991	0.987	0.995
Central t	0.991	0.994	0.990	0.976	0.996
Non-central t	0.926	0.953	0.950	0.748	0.910
Non-central t 2	0.992	0.995	0.991	0.976	0.997
Sample pre euro adoption					
Logistic	1.013	0.912	0.959	-	-
Central t	1.025	0.906	0.960	-	-
Non-central t	1.592	0.981	1.021	-	-
Non-central t 2	1.025	0.908	0.961	-	-
Sample post euro adoption					
Logistic	0.991	0.971	0.943	-	-
Central t	0.993	0.963	0.944	-	-
Non-central t	0.969	1.010	0.876	-	-
Non-central t 2	0.993	0.963	0.944	-	-

Table 8. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using perceived YoY inflation (π_t^p) as a scaling parameter. Actual inflation (π_{t-12}) has been used as a scaling parameter for quantifying perceived inflation. Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Logistic	0.994	0.986	0.979	0.992	0.993
Central t	0.992	0.981	0.977	0.984	0.994
Non-central t	1.011	1.017	0.997	0.936	0.969
Non-central t 2	0.992	0.980	0.977	0.983	0.994
Sample 2001.05-2019.12					
Logistic	0.987	0.981	0.985	0.993	0.999
Central t	0.984	0.967	0.976	0.986	1.003
Non-central t	1.095	1.076	1.040	1.016	0.947
Non-central t 2	0.983	0.965	0.975	0.985	1.003
Sample 2012.01-2019.12					
Logistic	0.982	0.949	0.982	0.979	0.996
Central t	0.987	0.947	0.976	0.960	0.998
Non-central t	1.129	0.989	1.142	1.010	0.936
Non-central t 2	0.986	0.946	0.974	0.959	0.997
Sample 2020.01-2023.07					
Logistic	0.998	0.990	0.976	0.991	0.992
Central t	0.997	0.990	0.977	0.983	0.992
Non-central t	0.974	0.984	0.979	0.830	0.972
Non-central t 2	0.997	0.989	0.977	0.983	0.992
Sample pre euro adoption					
Logistic	0.990	0.944	1.001	-	-
Central t	0.997	0.940	1.002	-	-
Non-central t	1.341	0.942	0.856	-	-
Non-central t 2	0.996	0.942	1.003	-	-
Sample post euro adoption					
Logistic	0.967	0.990	0.960	-	-
Central t	0.972	0.982	0.962	-	-
Non-central t	1.011	1.079	0.912	-	-
Non-central t 2	0.972	0.982	0.962	-	-

Table 9. RMSE ratio (assuming normal distribution divided by assuming indicated distribution) of quantified consumer inflation expectations using perceived YoY inflation (π_t^p) as a scaling parameter. Average of inflation from the beginning of the sample period to the time when the survey was conducted has been used as a scaling parameter for quantifying perceived inflation. Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Logistic	0.997	0.992	0.998	0.996	1.003
Central t	0.994	0.983	0.995	0.991	1.005
Non-central t	0.953	0.982	0.971	0.933	0.941
Non-central t 2	0.994	0.994	0.983	0.991	1.005
Sample 2001.05-2019.12					
Logistic	0.997	0.984	0.994	0.998	1.009
Central t	0.994	0.967	0.986	0.995	1.017
Non-central t	0.988	1.022	1.007	0.953	0.916
Non-central t 2	0.994	0.966	0.985	0.995	1.017
Sample 2012.01-2019.12					
Logistic	1.013	0.996	0.986	0.986	1.014
Central t	1.026	0.993	0.970	0.965	1.022
Non-central t	1.217	1.065	1.220	1.031	0.720
Non-central t 2	1.024	0.992	0.969	0.964	1.017
Sample 2020.01-2023.07					
Logistic	0.998	0.999	0.999	0.991	1.004
Central t	0.995	0.998	0.998	0.983	1.007
Non-central t	0.949	0.977	0.982	0.835	0.873
Non-central t 2	0.996	0.998	0.999	0.984	1.008
Sample pre euro adoption					
Logistic	1.011	0.947	1.018	-	-
Central t	1.021	0.947	1.018	-	-
Non-central t	1.723	0.940	0.995	-	-
Non-central t 2	1.020	0.947	1.018	-	-
Sample post euro adoption					
Logistic	0.993	1.000	1.001	-	-
Central t	0.993	1.000	1.001	-	-
Non-central t	0.995	0.997	0.801	-	-
Non-central t 2	0.993	1.000	1.001	-	-

When the scaling parameter used is actual inflation, non-central t distribution (with the non-centrality being the mean of consumer response balance statistics) provides some accuracy gains in a few of the tested samples. However, most of the accuracy gains compared to the normal distribution ranged from negligible in the case of the Estonian full sample to marginal gains of 6.4% in Lithuania when the sample from May 2001 to December 2019 is considered. The only considerable gains in accuracy were found in quantifying Lithuanian consumer inflation expectations in the samples 2012–2020 and 2012–2015, i.e. pre euro adoption sample.

Assuming a non-central t distribution yielded 62.3% more accurate quantified inflation expectations in terms of RMSE. Since the pre euro sample is included in the 2012–2020 period, the gains in accuracy might stem from the pre euro period. This period was characterized by unsubstantiated fears about the development of future prices, as seen by the balance statistics. Interestingly, no gains in accuracy were found in the period after the adoption of the euro. What is more, no such accuracy gains are found in Latvia or Estonia. As Latvia adopted the euro just one year prior to Lithuania, there is a lot of overlap in the periods tested. We see that the balance statistics dynamics were similar in both countries with high values before the adoption of euro and a drop off afterwards. The main difference can be seen in the dynamics of inflation itself – while the dynamics of inflation did not change in Lithuania much after the adoption of the euro, Latvia has experienced a drop in inflation levels. This could explain the difference in the accuracy gains before and after euro adoption. The drop in consumer expectations in Lithuania was not followed by the drop in inflation levels, whereas in Latvia it was. Hence, a downward push in inflation expectations by applying a non-central t distribution assumption yielded more accurate results during the period when expectations were high in Lithuania.

However, the same downward push to expectations did not do well in the most recent sample from January 2020 to July 2023. The accuracy of consumer inflation expectations were slightly worse compared to normal distribution in the Baltic countries but yielded notable accuracy losses in the case of Polish consumers during this period. Use of other distribution assumptions, namely - logistic, central t and other non-central t, did not have any non-negligible gains compared to normal distribution assumption in any of the periods under consideration. In the case when the scaling parameter is lagged actual YoY inflation rate π_{t-1} the results are very similar. RMSE ratios mirror the results of RMSE tables. Marginal precision gains are found in the Baltic countries during some of the periods tested with the exception of Lithuanian consumers during the pre euro period.

When the assumption about consumer inflation perceptions equaling actual inflation rate is dropped and CP method is applied to both inflation expectations and perceptions RMSE values are notably higher. However, the ratios do not differ significantly. I first discuss the results obtained by applying CP method to quantify consumer inflation perceptions while utilizing actual inflation rate (π_{t-12}) as scaling parameter for perceptions and the resulting consumer perceptions are used to scale inflation expectations. The use of quantified inflation perceptions results in comparable marginal gains in accuracy in the Baltic countries. The notable differences arise only in case of Estonia when considering the sample from 2012 to 2020. In this sample, the accuracy gains rise to 14.2% (from 4.5% and 4.0% when actual inflation or lagged inflation were used as scaling parameters, respectively). Also, precision gains from the pre euro sample in the case of Lithuania drop to 34.1%, suggesting that the use of non-central distribution was less beneficial.

Using running average of inflation as the scaling parameter for perceived inflation yields interesting results. The marginal precision gains in application of noncentral t distribution dampen in some of the samples studied; however, in the sample when the inflation was moderate (2012-2020) and pre-euro sample in the case of Lithuania, the accuracy gains are higher. Lithuanian consumer inflation expectations were 21.7%, Latvian – 6.5% and Estonian 22.0% more accurate when applying non-central t distribution in quantification of expectations in the period of 2012-2020. In the pre-euro sample, Lithuanian consumer inflation expectations were 72.3% more accurate when utilizing the above-mentioned distribution.

Overall, logistic, central t and non-central t distribution where the non-centrality parameter is constructed as the difference between latest official YoY inflation rate and the average YoY inflation rates in the previous 12 months did not provide any significant consumer expectation accuracy gains during the analyzed periods. There is evidence to suggest that the non-central t distribution where the non-centrality parameter is set using the mean of the balance statistics provided marginal accuracy gains in the Baltic countries during some periods under consideration. However, accuracy gains are more relevant when considering specific subsamples. That is, the sample from 2012 to 2020 yielded a more substantial precision of quantified inflation expectations in the case of Lithuania and Estonia. What is more, there was a significant improvement in the accuracy of expectations using non-central t distribution in Lithuania during the pre euro adoption period. If inflation dynamics stabilize and return to pre-Covid levels, using a non-central t distribution might be beneficial when considering the consumer responses in the Baltic countries. It is especially worthwhile considering the use of this

distribution assumption in a period of unsubstantiated high expectations about the development of future prices, as evidenced by the case of Lithuania during pre euro adoption.

Normal distribution assumption were the most consistently accurate for Polish consumer expectations with little benefit in applying different distributions. Whereas euro area aggregate consumer expectations were the most accurate with central t distribution. However, the accuracy gains are marginal (up to 2.2%). Such results for euro area are consistent with the findings of Lolic and Soric (2017) who find that central-t distribution is most accurate choice in the case of euro area in most of their tested quantification variations.

The results suggest that consumer inflation expectations do have a degree of heterogeneity in choice of distribution assumption. However, the application of normal distribution does not result in anything but marginal precision losses in most of the cases. What is more, while the choice of scaling parameter does have an effect on RMSE values, when considering the RMSE ratios of distributions, choice of scaling parameter do not alter the ratios significantly. This indicates, that the optimal choice of distribution should not change based on the choice of scaling parameter. Lastly, the only period analyzed with solid precision gains in quantified inflation expectations was in Lithuania before the adoption of the euro. Though, no accuracy gains are not present in the period after the change of the currency. However, the same result does not hold in the case of Latvia and Estonia. The results signify caution when analyzing the choice of distribution in countries undergoing currency transition as the optimal method might be different before and after the change.

3.3. Predictive Power of Quantified Consumer Inflation Expectations

Although both the graphs and the relatively high RMSE values in the Baltic countries suggest that quantified consumer inflation expectations are not very accurate in predicting the year-ahead inflation rate, they may still contain useful information for forecasting inflation. Therefore, it is important to test the predictive power of these expectations. To do so, this dissertation adopts a within-sample regression framework analogous to that used by Verbrugge and Zaman (2021) in their analysis of U.S. inflation expectation accuracy. The regression takes the below form:

$$\pi_{t+12} = \beta_1 \pi_{e,t+12} + \beta_2 \pi_t \quad (16)$$

Where π_{t+12} is actual year ahead inflation, $\pi_{e,t+12}$ is expected year ahead inflation and π_t is actual current period YoY inflation. As the authors explain, the goal of such regression is twofold. Firstly, it tests the coefficient estimate β_1 . The closer the value is to 1, the more accurate the consumer inflation expectations are. If the coefficient is not statistically significant, it would suggest that consumer expectations are not forward-looking and should not be used when forecasting year ahead YoY inflation. Secondly, it allows to test adjusted centered R squared ($R_{adj,c}^2$). $R_{adj,c}^2$ value of zero indicates that the models estimates are as good as using the mean of YoY inflation in terms of prediction accuracy. What is more, the measure also punishes for loss of degrees of freedom, hence $R_{adj,c}^2$ will only increase if consumer inflation expectations improve the model estimates significantly.

Therefore, I first run the regressions without the expectations to determine the baseline $R_{adj,c}^2$. I use the most accurate configuration of quantified inflation expectations (lowest RMSE) and balance statistics for all samples under consideration. As with Table 4, results for Estonia are not provided in the samples before and after euro adoption due to limited sample size. The results of the regression estimation are provided in Tables 10-11.

The results indicate that in the full sample quantified consumer inflation expectations were not significant in the case of Lithuania. What is more, the inclusion of expectations into the regression barely affects determination coefficient. This suggests that quantified consumer expectations have little predictive power when forecasting year ahead inflation rate. Similar situation can be observed in other countries as well. While β_1 coefficient is found to be significant⁵, the inclusion of expectations, does not change $R_{adj,c}^2$ by much. Best results is found in the case of Latvia, where $\Delta R_{adj,c}^2$ is the highest. What is more, in the case of Estonia, $R_{adj,c}^2$ is found to be negative, suggesting that the mean of YoY inflation was a better predictor of year-ahead inflation rate than the regression containing quantified consumer expectations as well as current inflation level. The use of balance statistics was preferred when forecasting inflation rate as the $\Delta R_{adj,c}^2$ was higher with the exception of Poland, where both quantified consumer expectations and their response balance statistics had similar predictive power.

⁵ Negative β_1 sign in some samples could be explained by Yule-Simpson effect, whereby the direction of a relationship observed in disaggregated data reverses once the data are aggregated.

Table 10. Regression results testing predictive power of quantified consumer inflation expectations. Significant at the 0.10 level (*); significant at the 0.05 level (**); significant at the 0.01 level (***). Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
β_1	-0.37	1.17***	0.46*	0.48**	-0.55*
$R^2_{adj,c}$	0.115	0.102	-0.101	0.448	0.118
$\Delta R^2_{adj,c}$	0.005	0.093	0.008	0.031	0.010
Sample 2001.05-2019.12					
β_1	0.09	1.60***	1.12***	0.30**	0.84***
$R^2_{adj,c}$	0.031	0.273	-0.142	0.107	-0.156
$\Delta R^2_{adj,c}$	-0.002	0.219	0.207	0.054	0.113
Sample 2012.01-2019.12					
β_1	-0.22	1.35***	-0.23	0.02	-0.097
$R^2_{adj,c}$	0.046	-0.094	0.150	0.254	0.192
$\Delta R^2_{adj,c}$	0.010	0.082	-0.004	-0.008	0.029
Sample 2020.01-2023.07					
β_1	-0.60	0.62	1.03	1.02	2.69***
$R^2_{adj,c}$	-0.181	-0.104	-0.138	0.430	0.308
$\Delta R^2_{adj,c}$	-0.025	-0.021	0.041	0.021	0.343
Sample pre euro adoption					
β_1	-0.79**	1.61***	-	-	-
$R^2_{adj,c}$	0.574	-0.174	-	-	-
$\Delta R^2_{adj,c}$	0.043	1.310	-	-	-
Sample post euro adoption					
β_1	2.44**	2.20**	-	-	-
$R^2_{adj,c}$	-0.027	-0.056	-	-	-
$\Delta R^2_{adj,c}$	0.203	0.244	-	-	-

Table 11. Regression results testing predictive power of balance statistics of consumer responses on inflation expectations. Significant at the 0.10 level (*); significant at the 0.05 level (**); significant at the 0.01 level (***). Source: Author's calculations.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
β_1	0.05***	0.14***	0.06***	0.05***	0.05***
$R^2_{adj,c}$	0.223	0.330	-0.014	0.459	0.157
$\Delta R^2_{adj,c}$	0.113	0.321	0.095	0.032	0.049
Sample 2001.05-2019.12					
β_1	0.04***	0.12***	0.15***	0.06***	0.01
$R^2_{adj,c}$	0.220	0.459	-0.130	0.259	-0.265
$\Delta R^2_{adj,c}$	0.187	0.405	0.219	0.206	0.004
Sample 2012.01-2019.12					
β_1	0.008	0.033***	0.004	0.009	0.021
$R^2_{adj,c}$	0.046	-0.046	0.146	0.258	0.173
$\Delta R^2_{adj,c}$	0.020	0.143	0.001	0.004	0.010
Sample 2020.01-2023.07					
β_1	0.143***	0.343***	0.087*	0.123***	0.136***
$R^2_{adj,c}$	0.236	0.462	-0.122	0.643	0.262
$\Delta R^2_{adj,c}$	0.392	0.545	0.057	0.234	0.297
Sample pre euro adoption					
β_1	-0.011**	0.145***	-	-	-
$R^2_{adj,c}$	0.556	-0.096	-	-	-
$\Delta R^2_{adj,c}$	0.026	1.388	-	-	-
Sample post euro adoption					
β_1	0.012	0.020***	-	-	-
$R^2_{adj,c}$	-0.238	0.165	-	-	-
$\Delta R^2_{adj,c}$	-0.008	0.465	-	-	-

Situation is similar when considering the first subsample (2001 May-2019 December) with the notable change in $R_{adj,c}^2$ for euro area consumer data and larger changes in $R_{adj,c}^2$ when including Latvian and Estonian consumer expectations in the regression. Looking into other analyzed samples – the results are not as straightforward. The significance of the coefficient is more difficult to determine due to a degree of collinearity between expectations and current inflation levels as well as a smaller sample size. The change in $R_{adj,c}^2$ after inclusion of expectations into regression is relatively small in most cases. The only exceptions are post euro adoption period and 2020.01-2023.07 sample for aggregate euro area expectations. Large $\Delta R_{adj,c}^2$ in Latvia during the pre euro adoption period should not be considered as high predictive power of quantified expectations rather than very poor fit of the baseline model. This result is corroborated by negative $R_{adj,c}^2$ suggesting that the mean of inflation was a better predictor of inflation than the regression fit. In fact, negative or close to zero $R_{adj,c}^2$ is obtained during multiple periods in the Baltic countries leaving much to be desired in terms of predictive power of quantified consumer inflation expectations. While both $R_{adj,c}^2$ and $\Delta R_{adj,c}^2$ improve when using balance statistics in a lot of samples tested, the coefficients obtained vary greatly between different periods. Thus, while the use of balance statistics improves the fit, it is not trivial forecasting inflation as the coefficient varies depending on the period.

Overall, the results suggest that quantified consumer inflation expectations do not have substantial predictive power in most cases. The main exception was the recent high inflation period for aggregate euro area expectations where expectations improved the regression fit considerably compared to the baseline model. This finding coincides with the conclusions from Mitchell and Zaman (2023) research on US consumers where researchers find that expectations accuracy increases when the inflation levels are higher. However, same conclusions cannot be made about the individual countries under consideration. The fit of the regression was best in the case of Polish inflation data. Yet, this is more due to baseline model being a better fit than in the case of Baltic countries rather than the predictive power of inflation expectations. While Verbrugge and Zaman (2021) find that quantitative US consumer expectations improve the baseline model the same cannot be concluded for quantified qualitative consumer responses for individual countries analyzed in this study.

3.4. Concluding Remarks

In this study I quantify qualitative consumer inflation expectations using Carlson-Parkin method applying different assumptions about the consumer response distribution and the scaling parameters for Lithuania, Latvia, Estonia, Poland and euro area as a whole. RMSE values suggest that non-central t distribution with the non-centrality parameter constructed as mean of balance statistics of consumer responses can provide marginal accuracy gains compared to normal distribution assumption in the case of the Baltic countries. Normal distribution assumption fits best in the case of Polish consumer expectations for most of analyzed configurations whereas aggregate euro area consumer inflation expectations are the most accurate when employing central t distribution which is consistent with the academic literature. In case of Poland and euro area as a whole, any accuracy gains are negligible though. Therefore, the cost of using non-optimal distribution assumption in terms of accuracy losses is small in most of the analyzed configurations.

The only substantial gains in precision using that non-central t distribution were achieved in the case of pre euro adoption period in Lithuania. Since the dynamics of inflation varied little before and after euro adoption, the use of non-central t distribution yielded considerably more accurate results as consumer response dynamics did shift significantly in the period after the euro adoption. It is especially worthwhile considering the use of this distribution assumption in a period of unsubstantiated high expectations about the development of future prices as evidenced by the case of Lithuania during pre euro adoption. RMSE values also suggest that choice of the scaling parameter has higher influence on the accuracy of quantified consumer inflation expectations compared to the choice of distribution assumption. However, measurement of accuracy rests on the assumption of consumer unbiasedness. It is entirely possible that actual consumer inflation expectations are not unbiased and the model selection based on these accuracy measurements do not indicate the true attitude of consumers. Nonetheless, considering the empirical application of consumer responses, lowest RMSE values might aid in selection of a model with best forecasting abilities. The choice of the scaling parameter had minimal effect on choice of distribution assumption though. When considering the precision of inflation expectations by measuring the RMSE ratios of distributions, choice of scaling parameter did not affect the ratios substantially. These findings are of particular importance to policymakers and economists focused on refining inflation forecasting tools.

The analysis of consumer response data suggests that consumers are forward-looking, but the horizon considered in their responses appears to be

shorter than 12 months. Cross-correlation suggests that the highest values are achieved for the 6-8 month horizon in the individual countries analyzed and about 4 months in the aggregate euro area data when the full sample is considered. However, the story is not as straightforward when short subsamples are considered. During the period from 2012 to 2020, Baltic consumers appear backwards looking, whereas Polish and aggregate data from euro area consumer responses indicate the highest correlation to current inflation levels. Similar results are found when testing the predictive power of quantified consumer expectations. Consumer expectations predictive power analysis suggests that quantified consumer expectations are not forward looking in the case of Lithuanian consumers and are not a good predictor of year ahead inflation when full sample is tested.

Analysis of subsamples suggests that quantified consumer expectations do not have substantial predictive power and did not substantially improve the baseline model in most configurations for all individual countries and the euro area. The only periods when quantified consumer expectations improved the baseline model considerably were the recent high inflation sample for the euro area and post euro adoption period for both Lithuania and Latvia. Additional research with regards to the comprehension of the consumer's time horizon, expectation formation, and their habits of information consumption could provide great benefits in explaining the findings.

4. COMPARATIVE EVALUATION OF CARLSON–PARKIN SPECIFICATIONS WITHIN A PANEL VAR FRAMEWORK FOR EU CONSUMER INFLATION EXPECTATIONS

Understanding inflation expectations has become critically important following the global inflationary episode that began in 2021, prompting renewed interest in their role within monetary policy frameworks. Traditionally viewed as crucial within modern macroeconomic frameworks, inflation expectations are theorized to influence actual inflation through aggregate demand and price-setting mechanisms.

However, recent literature indicates significant ambiguity concerning the strength and persistence of these relationships, especially concerning the expectations of consumers. Therefore, this study addresses three interrelated research objectives. Firstly, the study aims to empirically assess how consumer inflation expectations co-move with, and contribute to the dynamic interactions among, key macroeconomic variables across EU countries using a panel vector autoregression (PVAR) framework. Secondly, this research addresses methodological gaps by comparing commonly used balance statistics and different specifications of quantified expectations (Carlson-Parkin approach). Specifically, it critically evaluates whether the relationships identified are sensitive to different configurations of the Carlson-Parkin method. By systematically comparing multiple quantification specifications, the study sheds new light on the robustness of empirical conclusions on macroeconomic relationship inference, especially concerning consumer sentiment channel, and underscores the importance of methodological rigor when incorporating consumer expectations into macroeconomic analysis and policy recommendations. Thirdly, heterogeneity of inflation expectations effects to economy is checked on individual country level. While some studies focus on aggregate region data, such as euro area or EU, other studies focus on individual countries.

The results of this study suggest that there is a considerable amount of heterogeneity between different countries suggesting that aggregate approaches may obscure important cross-country differences.

4.1. Method

To analyze the dynamic relationships between macroeconomic variables, especially inflation expectations relation to other variables, I employ a Panel Vector Autoregression (PVAR) model. The choice of the method is motivated by the fact that the variables analyzed are interdependent and the use of VAR

allows modelling of such intertemporal dependencies. At first, PVAR with Fixed Effects is estimated using OLS, however, it has been documented that such models can suffer from endogeneity issues, namely, Nickell bias (Nickell, 1981). This bias is especially critical in cases when the longitudinal dimension (T) is small. While the data used in this research is quarterly from 2004Q1 to 2024Q3 for 26 countries⁶, some of the countries do not record observations for some of the variables from the beginning of the sample and the panel is unbalanced. The maximum T observations per country are 79 with the average of 65 observations. Therefore, Nickell bias should not be substantial, yet it will be tested by evaluating a second PVAR model using the two-step Generalized Method of Moments (GMM) as described by Sigmund and Ferstl (2017).

The specific form of the model estimation is system GMM, first described by Blundell & Bond (1998). Comparing the coefficients of the two models allows to assess the severity of endogeneity problem with the OLS model. The use of GMM does have its' own issues. The method uses lagged variables as instruments and can generate a large quantity of them leading to overfitting. In order to check for it, Hansen J test is performed to check the instrument validity. What is more, GMM is iterative making the method computationally intensive and given the sample, the lags included in the model need to be limited. Lastly, if the bias in the OLS PVAR model is not significant, GMM model can have significantly larger standard errors of the coefficients, making the variance-bias trade-off not a worthwhile one. General form of the PVAR model is given by:

$$Y_{i,t} = \Gamma_1 Y_{i,t-1} + \Gamma_2 Y_{i,t-2} + \dots + \Gamma_p Y_{i,t-p} + \Phi X_{i,t} + \alpha_i + \varepsilon_{i,t} \quad (17)$$

Where: $Y_{i,t}$ is a vector of endogenous variables for country i at time t ; Γ_j represents the coefficient matrices for lagged endogenous variables up to lag p ; $X_{i,t}$ is a vector of exogenous control variables (if included); Φ is the coefficient matrix associated with exogenous variables; α_i captures country-specific fixed effects; $\varepsilon_{i,t}$ is the error term.

⁶ Countries included in the sample: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden.

$$Y_{i,t} = \begin{bmatrix} C_{i,t} \\ Y_{i,t} \\ G_{i,t} \\ L_{i,t} \\ \pi_{i,t} \\ U_{i,t} \\ \pi_{i,t}^e \\ i_{i,t} \\ D_{i,t} \\ W_{i,t} \\ E_{i,t} \\ S_{i,t} \end{bmatrix} \quad (18)$$

Where $C_{i,t}$ is YoY percentage change in real consumption (CONS_YOY); $Y_{i,t}$ – YoY percentage change in real GDP (RGDP_YOY); $G_{i,t}$ - YoY percentage change in government spending (GS_YOY); $L_{i,t}$ - YoY percentage change in loans (LOANS_YOY); $\pi_{i,t}$ – YoY change in inflation rate (PI_YOY); $U_{i,t}$ - YoY change in unemployment rate (UN_YOY); $\pi_{i,t}^e$ - YoY change in inflation expectations (BS_YOY or PI_EXP_YOY); $i_{i,t}$ - YoY change in interest rate, EURIBOR 3M or equivalent for non-euro area countries (i _YOY); $D_{i,t}$ - YoY percentage change in household deposits (DEPOSITS_YOY); $W_{i,t}$ - YoY percentage change in average wage (WAGES_YOY); $E_{i,t}$ - YoY percentage change in energy prices (ENERGY_YOY); $S_{i,t}$ - YoY change in consumer confidence index (CCI_YOY).⁷ While the use of Year-over-Year (YoY) change variables ensure stationarity (Table 27, Annex B for Choi's modified unit root test), such choice is also beneficial in reducing the lags required to include in the computationally intensive GMM model to ensure appropriate residual serial correlation. The choice of the variables is motivated by the channels through which inflation expectations are theorized or measured to affect economies. For inflation expectations two different measures will be used – change in balance statistics of qualitative consumer responses to European Commission survey and quantitative year-ahead consumer inflation expectations quantified using canonical form of Carlson-Parkin method (See Berk (1999); Millet

⁷ CONS_YOY, RGDP_YOY, GS_YOY, PI_YOY, UN_YOY data is obtained from Eurostat. LOANS_YOY, i _YOY, DEPOSITS_YOY, WAGES_YOY data is obtained from ECB Data Portal. BS_YOY, CCI_YOY data is obtained from European Commission survey data.

(2006); Lyziak (2013) for elaborate description of the method). The lag order of one is used and the system of equations are as per below:

$$\left\{ \begin{array}{l} C_{i,t} = \gamma_{11}C_{i,t-1} + \gamma_{12}Y_{i,t-1} + \dots + \gamma_{1,12}S_{i,t-1} + \alpha_{1i} + \varepsilon_{1,t} \\ Y_{i,t} = \gamma_{21}C_{i,t-1} + \gamma_{22}Y_{i,t-1} + \dots + \gamma_{2,12}S_{i,t-1} + \alpha_{2i} + \varepsilon_{2,t} \\ G_{i,t} = \gamma_{31}C_{i,t-1} + \gamma_{32}Y_{i,t-1} + \dots + \gamma_{3,12}S_{i,t-1} + \alpha_{3i} + \varepsilon_{3,t} \\ L_{i,t} = \gamma_{41}C_{i,t-1} + \gamma_{42}Y_{i,t-1} + \dots + \gamma_{4,12}S_{i,t-1} + \alpha_{4i} + \varepsilon_{4,t} \\ \pi_{i,t} = \gamma_{51}C_{i,t-1} + \gamma_{52}Y_{i,t-1} + \dots + \gamma_{5,12}S_{i,t-1} + \alpha_{5i} + \varepsilon_{5,t} \\ U_{i,t} = \gamma_{61}C_{i,t-1} + \gamma_{62}Y_{i,t-1} + \dots + \gamma_{6,12}S_{i,t-1} + \alpha_{6i} + \varepsilon_{6,t} \\ \pi^e_{i,t} = \gamma_{71}C_{i,t-1} + \gamma_{72}Y_{i,t-1} + \dots + \gamma_{7,12}S_{i,t-1} + \alpha_{7i} + \varepsilon_{7,t} \\ i_{i,t} = \gamma_{81}C_{i,t-1} + \gamma_{82}Y_{i,t-1} + \dots + \gamma_{8,12}S_{i,t-1} + \alpha_{8i} + \varepsilon_{8,t} \\ D_{i,t} = \gamma_{91}C_{i,t-1} + \gamma_{92}Y_{i,t-1} + \dots + \gamma_{9,12}S_{i,t-1} + \alpha_{9i} + \varepsilon_{9,t} \\ W_{i,t} = \gamma_{10,1}C_{i,t-1} + \gamma_{10,2}Y_{i,t-1} + \dots + \gamma_{10,12}S_{i,t-1} + \alpha_{10i} + \varepsilon_{10,t} \\ E_{i,t} = \gamma_{11,1}C_{i,t-1} + \gamma_{11,2}Y_{i,t-1} + \dots + \gamma_{11,12}S_{i,t-1} + \alpha_{11i} + \varepsilon_{11,t} \\ S_{i,t} = \gamma_{12,1}C_{i,t-1} + \gamma_{12,2}Y_{i,t-1} + \dots + \gamma_{12,12}S_{i,t-1} + \alpha_{12i} + \varepsilon_{12,t} \end{array} \right. \quad (19)$$

4.2. Results

The first results discussed are when using balance statistics of consumer responses (BS_YOY). The coefficients obtained after estimating OLS fixed effects PVAR can be found in Table 28 (Annex B) and impulse response functions are provided in Figures 43-54 (Annex B). However, before discussing the results it is important to assess whether OLS estimated are affected by endogeneity. Therefore, the coefficients can be compared to GMM PVAR model (Table 29, Annex B).

First, comparison of the results reveals some significant differences in coefficients. OLS fixed effects PVAR model coefficient estimates are larger for several of the equations. The difference in magnitude is substantial enough that the coefficient becomes statistically insignificant in GMM model for some variables. Examples of this can be found with lagged real GDP growth (RGDP_YOY) effect on inflation expectations (BS_YOY) (0.5080, significant at $p < 0.001$ vs. 0.0466, significant at only $p < 0.05$) and government spending (GS_YOY) (0.1383, significant at $p < 0.01$ vs. -0.0156 with $p > 0.05$). As the focus of this research is on inflation expectations, notable differences in coefficient estimates can be found in lagged inflation expectations effect on other macroeconomic variables as well. While OLS estimates significant effect for consumption, loans, unemployment rate, interest rates and consumer confidence index, GMM estimates are insignificant; however, the effects in the OLS model are rather limited and the

change in significance level can be attributed to higher standard errors in the GMM model. Mainly, OLS models variables as more persistent than GMM, but GMM model estimates have significantly higher standard errors as expected. Hansen J test for GMM model fails to reject H_0 (p-value > 0.1) suggesting that the instruments used in GMM estimation are valid. However, this test should be taken with a grain of salt as the amount of variables used leads to a large number of instruments that can weaken the reliability of the estimates. Impulse response functions of GMM model can be found in Figures 55-66 (Annex B). Both the results of IRFs and coefficient significance point toward overparameterization, suggesting that GMM approach might not be more reliable than OLS results in this case where a model contains more than a few endogenous variables.

The impulse of the indicated variable is of one standard deviation impulse of the indicated variable. As per OLS model results, a shock in real consumption growth exhibits an immediate and strong positive response of approximately 3.67 p.p. in the first period and is quite persistent with the positive effect gradually decreasing to near-zero after about 6 quarters in the OLS model. Substantial responses are also found in real GDP growth increase (2.2 p.p.) with the effect lasting around 4 quarters, a decline in unemployment (-0.22 p.p.) converging to previous level in about 5-6 quarters, a mild but persistent (> 8 quarters) hump shaped positive response in inflation (0.56 p.p.) peaking at 4 quarters past the initial shock and a hump shaped response in energy prices reaching the peak (2.37 p.p.) in about 2-3 quarters. These responses to the real consumption growth shock are not surprising as they are in line with demand-side theories. Household loans experience a slight increase as a response to shock, however, it might be that households finance increased consumption via borrowing channel. When it comes to changes in consumer inflation expectations and confidence index, it can be observed that inflation expectations experience a hump shaped response with an initial increase (1.37 units) peaking with a one quarter delay (2.32 units) with the effect approaching zero in around 5 quarters. The effect, however, turns negative and significant in the longer horizon (>6 quarters). Such response suggests that consumer inflation expectations react to the shock with a bit of a delay to initial shock. This can happen due to several reasons. One of the possible explanations could rely on delay in information publicly available where some of the consumers react with a lag compared to others thus resulting in a hump shaped response. This could also happen if the consumer responses on inflation expectations react sensitively to increases in price levels, namely, change in inflation and energy prices in the case of this model. The return to previous expectations levels might indicate adjustment to the

persistent increase in both of those price level variables. Both reasons are valid as they are widely discussed in the economic literature. Consumer confidence index reacts to the shock in a similar fashion, but there is not hump in the reaction of it and the initial effect (1.64 units) tapers off at around second quarter. There is also a slight negative effect in the long term (> 4 quarters), but it is negligible. The GMM model, however, does not suggest such persistence of most of the variables. While the initial effect of one standard deviation shock to real consumption growth is stronger in GMM model (4.35 p.p.) it is not as persistent as it diminishes to zero in 2-3 quarters. Similar situation is indicated with real GDP growth – stronger initial reaction (3.41 p.p.) but the effect tapers off in 2-3 quarters. Overall, the IRFs of GMM model have large standard errors, therefore, the 95% confidence interval for the responses of other variables includes zero, meaning that the effect found is not statistically significant. Consumer inflation expectations and confidence index are a bit more persistent than the OLS model suggests, but as mentioned, insignificant at the 5% level. The dynamics of responses to a shock in real GDP growth are analogous to responses to a shock in real consumption growth in both models. Slight differences arise in the magnitude of the responses. OLS model suggests that a shock to RGDP_YOY results in a 2.87 p.p. initial response in real consumption and 2.81 p.p. in real GDP growth lasting up to 6-7 quarters. Response of change in consumer inflation expectations are 1.34 units in the initial period, peaking at 2.6 units. GMM model suggests an initial response to the change in real consumption growth of 2.38 p.p. and 6.25 p.p. for real GDP growth.

When considering a positive shock to government spending, the responses of the other macroeconomic variables are much less pronounced. OLS PVAR model results indicate that in the case of a one standard deviation shock to GS_YOY, real consumption growth responds with around 0.37 p.p. initial increase with the effects peaking in 2-3 quarters (0.5 p.p.) after the shock and lasting up to 6 quarters. This suggests that increased government spending has a stimulative effect on consumer demand. Real GDP growth exhibits a comparable response dynamic with a slightly lower magnitude. The government spending growth itself is indicated as persistent with the initial response of 3.87 p.p. and lasting around 8 quarters. There is a minor effect of the shock on wages growth peaking in 2-3 quarters (0.7 p.p.), however such results are most likely obtained since part of the government spending is associated with wages of employees in the public sector rather than the mechanism of the shock transmission itself. Growth of household loans appear to have a significant response as well. Yet, the confidence interval is rather wide implying that the effect of government spending on household debt

might vary. Other variables do not have statistically significant responses suggesting limited transmission mechanisms of government spending shocks. GMM model results indicate that a shock in government spending only significantly affects wage growth.

OLS model results show that a shock in YOY inflation is indicated as highly persistent lasting longer than 8 quarters. Responses from real consumption growth and real GDP growth are more likely to be one of the causes for the inflation increase through aggregate demand channels rather than responding to an increase in price level. Similar can be said about energy prices – it is more likely that an unexpected increase in the energy prices is the cause of inflation shock rather than the other way around. Wages do not initially respond to a shock in inflation – significant responses are only indicated in about 3-4 quarters after then initial shock. However, even then the response is very mild (around 0.25 p.p.) and far less than the inflation shock. This suggests that in the time period analyzed the wage-price spiral was not a prominent shock transmission mechanism. These results are corroborated by response in household deposits. There is no initial response in the change of household deposits after the shock, but a significant negative effect appears in about 2-3 quarters (-0.25 p.p.) and persists long term (about -0.67 p.p. 8 quarters after the shock). This hints that unexpected rise in prices is offset by household savings. Initially consumer inflation expectations increase (3.39 units) as a response to the shock, but after 3 quarters from the initial shock expectations come back to the level before it. In the longer horizon this shock has a negative impact on expectations (-2 units) suggesting that consumers adjust to new price level quickly and expect it to return to previous levels in the long term. Consumer confidence index reacts negatively (-1.1 unit) to a positive inflation shock but returns to previous levels in 6 quarters.

An unexpected increase in the unemployment level is persistent and lasts up to 8 quarters. As expected in economic theory, such shock has strong negative responses of real consumption and real GDP growth (-1.28 p.p. and -1.1 p.p. initial responses, respectively). The YoY growth rates of both the variables return to previous levels in around a year and a half. The shock does not have an initial effect on the wage growth rate, however, 2 quarters after initial shock wage growth rate experiences a negative persistent effect (up to -0.45 p.p.). What is unexpected, is that inflation does not have a noteworthy response to this shock. The response (0.1 – 0.16 p.p.) is barely significant at 95% level. Such findings are not in line with the economic theory. Theoretically, Phillipps curve and a reduction in aggregate demand should pressure price level downwards, however, the results do not suggest that. This could, however, indicate that the countries analyzed had unemployment levels

higher than inflation accelerating level throughout the time period in consideration. Both consumer inflation expectations and confidence index respond similarly. An initial minor contraction (-0.92 units and -1.28 units), returning to previous levels in 3 quarters.

A one standard deviation increase in consumer inflation expectations balance statistics has some minor positive effects on real consumption growth with the initial effect of 0.42 p.p. but decreasing and diminishing in 3 quarters. However, in the longer term (5-8 quarters) the effect turns negative with similar magnitudes. This is in line with the economic theory, suggesting that consumers expecting higher inflation levels in a year's time move part of their future consumption to the present. Similar effect can be observed in changes of the real GDP growth. The shock has effect on the changes in balance statistics of consumer inflation expectations itself for about 4 quarters which is expected due to the nature of how the expectations data is collected, namely, the nature of the question to respondents having a reference level of current inflation. What is interesting, is that after 5 quarters of the response turns negative but of much lower magnitude than the shock itself. This suggests once the shock has happened, balance statistics remain on a higher level for a prolonged time, i.e. while consumers expect the inflation to decrease, they believe it will take some time before it returns to previous levels. Inflation reacts with an immediate 1.11 p.p. increase to a shock that decreases over time but is highly persistent with the effects indicated to last > 8 quarters. Supporting the previous findings on inflation shock, wages growth rate does not react to an expectations shock as well. This corroborates, that wage-price spiral was not a present shock transmission mechanism in the period analyzed. Consumer confidence react negatively to the shock and the effect lasts for about two years.

A shock to consumer confidence index indicates positive effects to aggregate demand and displays responses generally expected from economic theory standpoint. The balance statistics of consumer inflation expectations initially respond with a decline (-3.87 units) but in the second quarter after the shock the effect is insignificant and onwards the effect turns positive, i.e. inflation expectations increase, peaking (2.63 p.p.) 4 quarters after initial shock. Such results might be influenced by the response of energy prices found with the model though, which is more likely to be influenced by the period as it is hard to believe energy prices would decrease after consumer confidence index hike. A one-way relationship the other way around is more likely. Overall, the results indicate several findings. Firstly, notable discrepancies are recorded in OLS and GMM models with OLS suggesting higher degree of persistence and stronger relationships between the variables

whereas GMM estimates find significantly higher standard errors leading to statistical insignificance. Impulse response functions indicate that shocks in real consumption and real GDP positively impact aggregate demand indicators aligning well with economic theory. Government spending shock results, however, suggest limited and less significant effects across multiple macroeconomic variables. Shocks to inflation expectations initially boost real consumption and inflation but eventually generate negative feedback, suggesting consumers shift their consumption forward anticipating future price increases. Wage-price spirals were notably absent as a transmission mechanism during the analyzed period, highlighting weak responsiveness of wages to inflationary pressures. Lastly, unemployment shocks exhibited strong negative effects on consumption and GDP growth but surprisingly limited effects on inflation, challenging traditional Phillips curve predictions, potentially indicating structural unemployment conditions above inflation-accelerating levels in the studied economies. These findings underscore the nuanced interplay between macroeconomic indicators and consumer sentiment, highlighting the need for careful model selection and interpretation when analyzing macroeconomic policy implications.

4.2.1. Carlson-Parkin Method and Panel Vector Autoregression

Before presenting the empirical results, it is necessary to outline how the Carlson–Parkin method is incorporated into the panel VAR framework. The purpose of this subsection is to examine whether quantified consumer inflation expectations retain informational content once embedded in a multivariate macroeconomic setting and whether this content depends on the choice of scaling parameter. Since the CP method requires a distributional assumption and a specific calibration of the scaling factor, alternative specifications may generate materially different expectation series. For this reason, the analysis below evaluates several commonly used scaling approaches and considers how the resulting quantified expectations behave within the dynamic structure of a panel VAR.

The following are results when qualitative consumer inflation expectation responses are quantified using Carlson-Parkin method. Normal distribution is assumed, and three scaling parameters are used. The first scaling parameter is actual YoY inflation. While this scaling parameter is popularly used in the literature (Berk, 1999, Forsells and Kenny, 2002, Lolic and Soric, 2017, etc.), it does have its' drawbacks. The use of this scaling parameter implies that consumers correctly perceive current rate of inflation. However, studies suggest that it is not always the case. The second scaling

parameter used is running average rate of inflation. It assumes that consumers approximate inflation rate from the information available but are not always up to date in their views on what the current inflation rate is. In other words, consumers possess a general awareness of past inflation developments and adjust their expectations accordingly, albeit in an imprecise and delayed manner. This parameter relaxes the strict unbiasedness assumption inherent in the Carlson-Parkin method, while still presuming that consumers broadly perceive past inflation accurately, though with a greater degree of inertia or inattention. Two years period for running average calculation is used in this study for the second scaling parameter. The third approach involves the estimation of consumers' perceived inflation by applying the Carlson-Parkin method to qualitative survey responses regarding perceptions of year-on-year inflation. This procedure necessitates the use of a scaling parameter to represent a "moderate" rate of inflation, as consumers are asked in reference to such a rate. The most commonly adopted proxies for this moderate inflation rate in the literature are either the central bank's inflation target (Lolic and Soric, 2017) or a running average of past inflation (Szyszko and Rutkowska, 2019, Lyziak, 2010, Szyszko, Rutkowska and Kliber, 2019, etc.). This approach has been the most popular in recent studies utilizing Carlson-Parkin method. Accordingly, in this study, the third scaling parameter is defined as the quantified consumer perceived inflation rate, calculated using a two-year running average of actual inflation.

Figures 67–72 (Annex B) represent impulse response functions from PVAR models when the expected inflation used is quantified using Carlson-Parkin method. To limit the discussion of results, only response of other macroeconomic variables to inflation expectations shock and inflation expectations response to other variable shocks will be presented.

The impulse response analysis comparing models using the change in balance statistics (BS_YOY) and those using quantified consumer inflation expectations (PI_EXP1_YOY) reveals broadly similar macroeconomic dynamics across most variables. As expected, the behavior of the inflation expectations variable itself differs notably between the two specifications, reflecting the differing measurement of the variables. Beyond this, no substantial differences in the dynamic responses of other variables are observed. Although subtle divergences can be noted. The first one can be seen in the response of the consumer confidence index (CCI_YOY) to a shock in unemployment. Although the initial response is comparable across both models, the specification using quantified inflation expectations indicates a positive long-term effect, beginning after approximately five quarters, with magnitudes reaching 0.3 to 0.4 units. Another notable difference occurs in the

response of year-on-year changes in household deposits to a shock in inflation expectations. In the BS_YOY model, the response is statistically insignificant. In contrast, the PI_EXP1_YOY model produces a significant negative effect, with deviations of up to -0.7 percentage points appearing after the fourth quarter. Minor differences in the magnitude of responses are also observed in selected variables, though these do not indicate substantial changes in direction or persistence. When comparing the BS_YOY model to the model using quantified expectations constructed with a scaling parameter equal to the running average of actual year-on-year inflation (PI_EXP2_YOY), the overall dynamics again remain largely similar. However, some additional differences do arise. Specifically, the responses of energy prices (ENERGY_YOY) and consumer confidence (CCI_YOY) exhibit greater persistence in the PI_EXP2_YOY model. The relationships between energy prices, inflation, and inflation expectations are more prolonged, indicating that the inflation transmission channel through energy prices may be more strongly activated when using quantified expectations.

Additionally, CCI_YOY responses to several shocks are of greater magnitude and return to pre-shock levels more slowly, suggesting that consumer sentiment dynamics may be affected by the specification of inflation expectations. This observation is further corroborated by findings from the final model, which uses perceived inflation expectations to quantify consumer views (PI_EXP3_YOY). In this specification, consumer confidence does not respond significantly to a shock in inflation expectations, diverging from the earlier models. Moreover, a positive shock to CCI_YOY results in a positive and persistent response of inflation expectations, whereas previous models exhibited an initial negative response under the same shock. This reversal implies that the sentiment channel is particularly sensitive to both the measurement and quantification specification of inflation expectations. The final model also demonstrates that although the broader dynamics remain similar, actual year-on-year inflation (PI_YOY) reacts with roughly half the intensity to a shock in inflation expectations compared to previous specifications. This finding underscores that the nature and intensity of macroeconomic adjustment processes are meaningfully influenced by the formulation of the expectations channel. Among all observed channels, consumer sentiment appears to be the most sensitive, with implications for the responsiveness of other variables. In sum, these results highlight the importance of how inflation expectations are modelled in empirical macroeconomic research. The findings suggest that the choice of expectations proxy, whether qualitative or various forms of quantified expectations, can shape the inferred strength and persistence of macroeconomic relationships,

particularly through the sentiment channel. This can have important consequences for both inflation forecasting and the interpretation of expectations in research and policy.

4.2.2. Forecast Error Variance Decomposition

The forecast error variance decomposition analysis of our model, which utilizes business statistics as a proxy for consumer inflation expectations (as depicted in Figures 73-75 (Annex B), reveals several key insights into the dynamics of macroeconomic variables. The variance in real consumption, government spending, household loans, and household deposits is predominantly explained by shocks to the respective variables themselves, with more than 85% of the variance accounted for within an eight-quarter horizon following the initial shock.

In the case of real GDP growth, a significant proportion of its variance is influenced by shocks to consumption. Initially, this effect is substantial at 61.1%, although it diminishes over time to approximately 43% by the eighth quarter. Conversely, the explanatory power of real GDP growth itself increases from an initial 38.9% to about 44.8% over the same period, highlighting persistent self-influence. Additionally, the consumer confidence index becomes increasingly relevant, contributing up to 6.9% of the variance by the eighth quarter. The variance decomposition of inflation (PI_YOY) is initially dominated by its own shocks.

However, as the horizon expands, consumption and consumer inflation expectations become more critical in explaining the variance, contributing 20.2% and 15.2%, respectively. Changes in the unemployment rate are largely driven by exogenous shocks to itself initially. Over time, however, shocks to consumption (14.4%) and real GDP (17.5%) increasingly influence unemployment dynamics, underscoring strong interactions between labor market conditions and overall economic activity. Consumer confidence also emerges as a significant factor, contributing 10.4% of the variance, indicating its psychological and behavioral influence on employment decisions. The consumer response balance statistics are initially heavily influenced by exogenous shocks to themselves. Although, the explanatory power of real consumption growth, actual inflation, and consumer confidence grows over time, reaching 5%, 9.1%, and 9.7%, respectively, by the eighth quarter. Similarly, wages are increasingly influenced by real consumption and real GDP, with contributions of 8.4% and 4.5% at the eighth quarter. Government spending also plays a role, maintaining an explanation power of around 12% one year after the shock. As expected by economic theory, interest rate

changes are primarily influenced by macroeconomic variables over longer horizons. Real consumption explains 6% of the variance, real GDP accounts for 14.4%, and inflation explains 8.2%, while consumer expectations contribute up to 5.8%. The variance in energy prices is closely tied to actual inflation levels both initially and over time, with real consumption becoming a more important factor in the longer term. Lastly, the variance in the consumer confidence index is primarily driven by its own shocks. However, consumer attitudes towards future price developments can explain up to a quarter of the variance starting from the fourth quarter. Inflation and real consumption also become more significant over longer horizons, explaining 6.4% and 4.8% of the variance, respectively. This suggests that consumer sentiment is sensitive to price levels and overall consumption patterns.

4.2.3. Vector Autoregression on Individual Countries

A central methodological question in the empirical literature is whether panel data analysis or country-specific estimation provides more informative insights into macroeconomic dynamics. In this study, the same model specification utilized in the panel setting is applied to individual countries in order to examine potential heterogeneity in responses. Specifically, for each country, a vector autoregression (VAR) model is estimated, and impulse response functions (IRFs) with associated 95% confidence intervals are computed. Given the focus of this research on consumer inflation expectations, the analysis concentrates on the dynamic interactions captured by the panel VAR and on how macroeconomic variables react to orthogonalized innovations in quantified expectations. Table 12 summarizes the country-specific IRFs for the percentage change in real consumption (CONS_YOY), change in inflation (PI_YOY), wage growth (WAGES_YOY), and variation in the Consumer Confidence Index (CCI_YOY) in response to a one standard deviation shock in consumer inflation expectations response balance statistics (BS_YOY).

Table 12. Summary of VAR impulse response functions of select macroeconomic variables to a positive shock of inflation expectations (*BS_YOY*) for individual countries.

	Negative response	Delayed negative response	No significant response	Delayed positive response	Positive response
Real Consumption growth (CONS_YOY)	-	-	AT, BE, BG, CZ, ES, FR, GR, HR, HU, IT, LT, LU, NL, PL, PT, RO, SI, SK	-	CY, DE, EE, FI, IE, SE
Inflation (PI_YOY)	-	-	NL, SI	CZ, HU, IT	AT, BE, BG, CY, DE, EE, ES, FI, FR, GR, HR, IE, LT, LU, PL, PT, RO, SE, SK
Wage growth (WAGES_YOY)	-	ES	AT, BG, CY, CZ, DE, FI, FR, GR, HR, IE, IT, LT, LU, NL, PL, PT, RO, SE, SI, SK	BE	EE, HU
Consumer Confidence Index (CCI_YOY)	AT, BE, BG, CY, CZ, DE, ES, FR, GR, HR, HU, IT, LT, LU, PL, PT, RO, SI, SK	FI, NL, SE	IE	-	EE

The results indicate that only a minority of countries display a positive consumption response to an inflation expectations shock, with Finland being the sole country to exhibit a persistent effect beyond the initial period. In contrast, the panel model suggests a modest positive consumption effect lasting up to three quarters, yet most country-level VAR estimates do not support a statistically significant or sustained increase in consumption in response to heightened inflation expectations. Turning to inflation dynamics, the majority of country-specific responses are consistent with the aggregate panel findings. A positive expectations shock is generally associated with an increase in YoY inflation, typically following a hump-shaped trajectory of similar duration. However, some exceptions are observed, notably in the Czech Republic, Hungary, and Italy, where inflation responses are delayed, and in the Netherlands and Slovenia, where the estimated effects are statistically insignificant. Analysis of wage growth reveals that most countries do not exhibit systematic responses to changes in inflation expectations. However, in the cases of Estonia and Hungary there is a positive response in wages while in the case of Belgium there is a delayed positive effect. Conversely, Spain demonstrates a significant negative relationship, which may be attributable to structural labor market conditions, such as persistently high unemployment relative to the EU average. Nonetheless, the magnitude of these wage responses remains limited. With respect to consumer sentiment, as proxied by the Consumer Confidence Index, most countries mirror the negative response observed in the panel analysis. However, these effects are generally less persistent at the country level, with significant negative impacts persisting beyond the third period in only about half of the sample. Notably, Finland, the Netherlands, and Sweden exhibit delayed responses, while Estonia displays a short-lived positive effect. Collectively, these findings highlight substantial heterogeneity in the intensity, statistical significance, and persistence of macroeconomic responses to inflation expectation shocks across countries. This heterogeneity underscores the value of country-specific analysis for understanding the transmission of inflation expectations to macroeconomic outcomes, suggesting that aggregate panel approaches may obscure important cross-country differences.

4.2.4. Concluding Remarks

This study presents the critical importance of accurately modelling consumer inflation expectations in macroeconomic analysis, highlighting several key points. Firstly, there is a significant relationship between inflation expectations and consumer spending behavior consistent with the

intertemporal substitution effects asserted in theoretical models. The impulse response analyses revealed theoretically consistent, yet empirically modest effects of inflation expectations on aggregate demand and actual inflation. A critical observation was the persistent absence of the wage-price spiral during the analyzed period, indicating limited transmission from inflation expectations to wage dynamics. Furthermore, contrary to conventional Phillips curve expectations, unemployment shocks exhibited only marginal effects on inflation, suggesting structural labor market dynamics such as unemployment rate above the natural rate of unemployment. The results could also indicate that during the period analyzed inflation was prominently influenced by supply side shocks rather than demand. Furthermore, the sensitivity analysis utilizing different quantification methods for qualitative inflation expectation responses illustrated that macroeconomic relationships found, particularly concerning consumer sentiment and spending behavior, are dependent on methodological choices. This study highlights that consumer sentiment dynamics display substantial sensitivity to the specific method employed for quantifying inflation expectations. Therefore, research focusing on consumer sentiment should exercise caution when selecting methods to quantify consumer inflation expectations, or alternatively, should verify the robustness of results by testing multiple quantification approaches. What is more, consumer inflation expectations dynamics and effects have considerable heterogeneity between the countries. Hence, most accurate results can be found studying the effects of consumer behavior to macroeconomics in the context of individual countries.

5. SOCIO-DEMOGRAPHIC HETEROGENEITY: SUBGROUP-BASED QUANTIFICATION AND ACCURACY IMPROVEMENT

Chapters 1 and 2 provide a review of the relevant literature, highlighting several important determinants of consumer inflation expectations. First, existing research consistently identifies an upward bias in both the perceptions and expectations of inflation, suggesting that households tend to systematically overestimate price developments relative to official measures. Second, substantial heterogeneity exists across individuals, shaped by their socio-demographic characteristics as well as their personal experiences with inflation. Survey responses from the European Commission's Business and Consumer Surveys (EC BCS) provide data defined by various subgroups such as age cohorts, income quartiles, gender, and educational attainment. Recognizing both the systematic bias and subgroup heterogeneity is particularly valuable when applying the Carlson–Parkin (CP) method to quantify qualitative household responses. By first addressing subgroup-specific biases and differences, one can transform qualitative assessments of inflation into meaningful quantitative estimates at the subgroup level, which can subsequently be aggregated to yield more representative results for the population as a whole. This two-step approach contrasts with the standard practice in the literature, which typically aggregates responses prior to adjustment, thereby neglecting underlying heterogeneity. To the best of my knowledge, no published studies have explicitly adopted a framework that corrects for subgroup-level variation before aggregation in the quantification of consumer perceptions and expectations of inflation.

The remainder of this chapter proceeds as follows. Section 5.1 introduces the dataset, with a particular focus on Lithuanian household survey responses. Section 5.2 describes novel application of CP method. Section 5.3 applies the described method to quantify perceptions of inflation, and evaluates the gains in accuracy that result from addressing subgroup heterogeneity. It also extends the analysis to the broader euro area, applying the same methodological framework.

5.1. Lithuanian Household Data

The analysis begins with an examination of Lithuanian household survey responses, with particular attention to Questions 5, 6, and 9 of the European Commission's Consumer Survey, as well as the Consumer Confidence

Indicator (CCI), which is derived from a composite of responses to Questions 1, 2, 4, and 9. These questions are presented below for clarity:

***Q1** How has the financial situation of your household changed over the last 12 months?*

***Q2** How do you expect the financial position of your household to change over the next 12 months?*

***Q4** How do you expect the general economic situation in this country to develop over the next 12 months?*

***Q5** How do you think that consumer prices have developed over the last 12 months?*

***Q6** By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?*

***Q9** Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months?*

Since the survey elicits qualitative answers on a five-point categorical scale, the analysis employs balance statistics (BS), which transform categorical responses into a continuous indicator reflecting the balance of positive versus negative assessments. This method enables systematic comparison of household sentiment across time and subgroups. The data are disaggregated by several socio-demographic characteristics to capture potential heterogeneity in consumer perceptions and expectations. The subgroup classifications are as follows: **Age cohorts:** AGE1 (15–29), AGE2 (30–49), AGE3 (50–64), AGE4 (65+). **Income quartiles:** four equal-sized groups based on reported household income with the first quartile being the lowest income households. **Educational attainment:** EDUC1 (less than primary, primary, and lower secondary; ISCED 2011 levels 0–2), EDUC2 (upper secondary and post-secondary non-tertiary; ISCED 2011 levels 3–4), EDUC3 (tertiary education; ISCED 2011 levels 5–8). **Gender:** Male, Female.

The period under consideration extends from January 2011 – when subgroup-level data were first released - through May 2025. Table 13 presents the balance statistics for the age subgroups, while Figures 12-15 illustrate their dynamics over time. The results reveal several salient patterns. With respect to inflation perceptions (Q5), the youngest cohort (AGE1) consistently reported the lowest perceived inflation over most of the sample period. By contrast, the AGE2 cohort tended to report somewhat higher inflation perceptions than AGE1, though still lower than those of AGE3 and AGE4. Interestingly, the two oldest groups (AGE3 and AGE4) display broadly similar dynamics, suggesting convergence of perceptions among older respondents. During the recent inflation surge, the distinction between groups

narrowed: only AGE1 continued to report somewhat lower perceived inflation, whereas the perceptions of AGE2–AGE4 evolved along nearly parallel trajectories. Turning to inflation expectations (Q6), the results indicate less pronounced heterogeneity across age groups. The dynamics of the balance statistics suggest that all cohorts broadly share similar expectations regarding future price developments. Although AGE1 occasionally reports slightly lower expectations of price growth, these deviations are limited in both magnitude and duration. Thus, while inflation perceptions exhibit significant age-related heterogeneity, inflation expectations appear more homogeneous.

The Consumer Confidence Indicator reflects dynamics closely aligned with inflation perceptions. Younger households, particularly AGE1, display a systematically more optimistic outlook on the economic situation and household finances throughout the entire period. AGE2 respondents are somewhat less optimistic but nevertheless report more favorable assessments compared to AGE3 and AGE4. The two older cohorts consistently exhibit the most pessimistic outlook, reinforcing the observation that age is strongly associated with differences in consumer sentiment. Finally, responses to Question 9 (expected spending on durable goods) display particularly interesting subgroup dynamics. In the initial years of the sample, age differences in expected durable consumption are limited, with little distinction across cohorts. However, over time, clear divergence emerges: younger cohorts (AGE1 and AGE2) increasingly report stronger intentions to raise spending on durables, while older cohorts exhibit more restrained consumption plans. This pattern suggests that forward-looking consumption behaviour is not only sensitive to macroeconomic developments but also shaped by lifecycle factors.

Table 13. Balance statistics means of Lithuanian households by subcategory - age. Sample period 2011.01-2025.05.

	AGE 1	AGE 2	AGE 3	AGE 4
Q5	42.62	50.42	54.32	55.40
Q6	36.90	39.70	41.37	36.74
CCI	6.25	-2.46	-8.59	-9.40
Q9	6.80	1.06	-3.89	-7.79

Figure 12. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory - age.

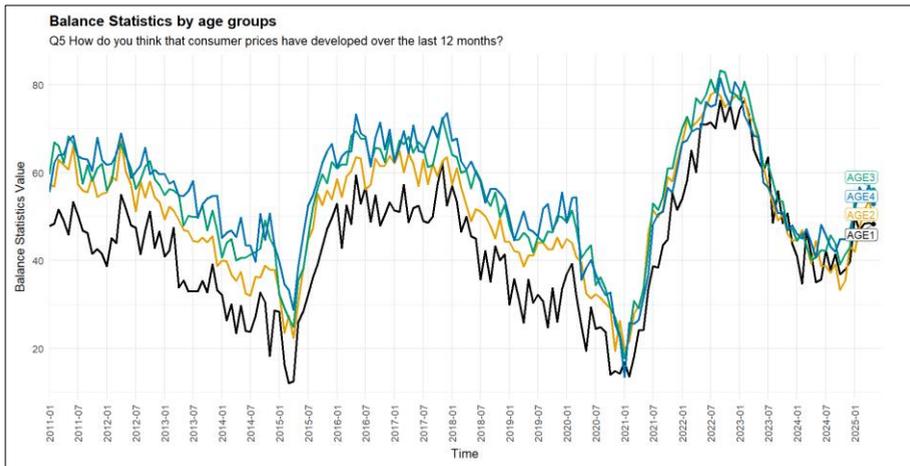


Figure 13. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - age.

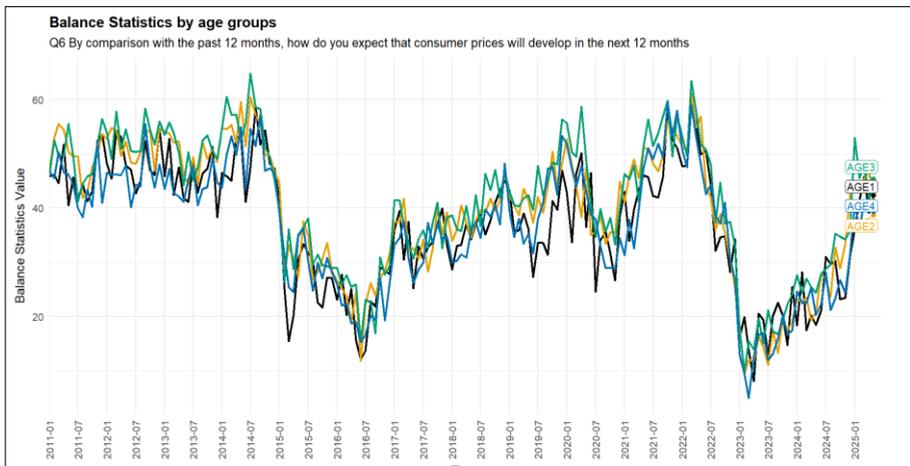


Figure 14. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - age.

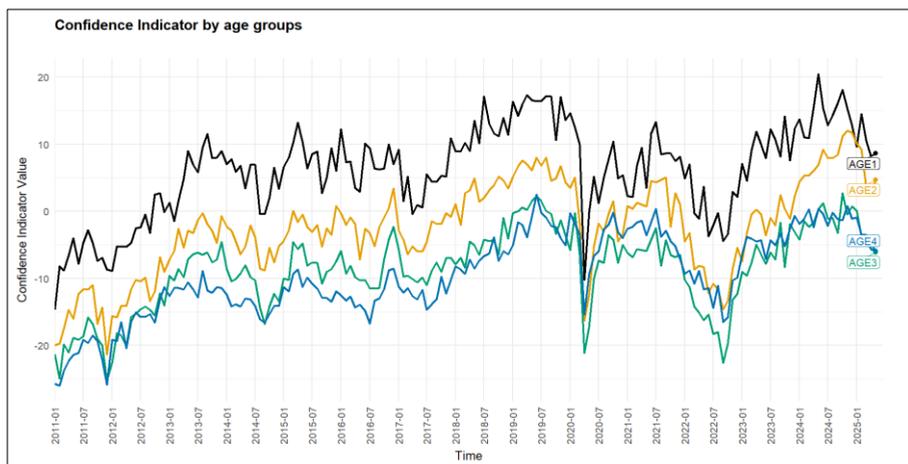


Figure 15. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - age.

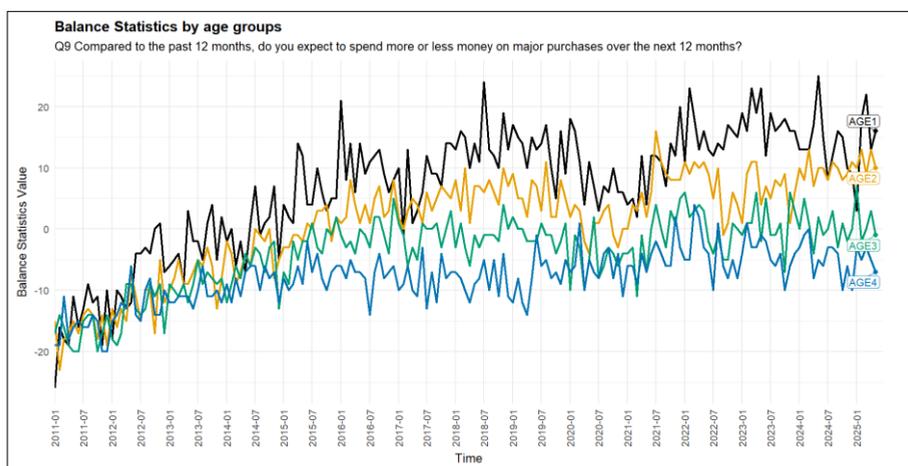


Table 14 reports the balance statistics for income-based subgroups, while Figures 16–19 illustrate the temporal dynamics of these responses. In comparison with age-based disaggregation, income-related heterogeneity in consumer sentiment appears more pronounced. A clear and consistent pattern emerges: households in the highest income quartile (INCOME4) demonstrate the most optimistic responses across nearly all survey questions. On average, they report the lowest perceived inflation levels and expect inflation to remain lower in the future relative to other income groups. Nevertheless, a closer inspection of the time dynamics reveals periods during which even INCOME4 respondents exhibit expectations broadly aligned with those of lower-income

quartiles, suggesting that optimism among high-income households is neither uniform nor immune to broader macroeconomic shocks. When comparing inflation perceptions across quartiles, a negative gradient becomes apparent: higher income is systematically associated with lower reported inflation. However, this relationship does not extend as clearly to inflation expectations. For the lower three quartiles (INCOME1–INCOME3), average expectations and their dynamics are largely indistinguishable. This finding indicates that while perceptions of past inflation exhibit a strong income gradient, forward-looking expectations are less sensitive to income differences. The Consumer Confidence Indicator (CCI) reinforces the pattern of income-related optimism. Higher-income households consistently provide more favorable assessments of household finances and the economic outlook, and this positive bias persists throughout almost the entire observation period. In contrast, lower-income households systematically exhibit greater pessimism, underscoring the importance of financial resources in shaping broader economic sentiment. Differences are also evident in responses to Question 9 concerning planned expenditure on durable goods. On average, households in the lowest income quartile (INCOME1) anticipate reduced consumption, whereas those in the highest quartile (INCOME4) expect to increase their durable purchases. The dynamics are particularly telling: INCOME1 respondents exhibit only a handful of periods with positive balance statistic values, indicating consistently low expectations of increased durable consumption. By contrast, INCOME4 responses are frequently positive, highlighting a sustained confidence in their ability to expand consumption. Middle-income households (INCOME2 and INCOME3) display considerable overlap in their response trajectories, with only temporary divergences that rarely persist beyond a few months.

While the observed heterogeneity across income quartiles is substantial, one important caveat should be noted. Income-based subgrouping is especially susceptible to mobility across quartiles over the period of analysis. Households experiencing upward mobility - through higher earnings, improved employment prospects, or favorable financial conditions - may shift into higher income quartiles, thereby biasing responses within those subgroups toward more optimistic assessments. Conversely, downward mobility could reinforce pessimism among lower quartiles. Thus, the apparent differences between income groups not only reflect genuine disparities in household sentiment but may also be influenced by changes in the composition of the subgroups themselves.

Table 14. Balance statistics means of Lithuanian households by subcategory - income. Sample period 2011.01-2025.05.

	INCOME 1	INCOME 2	INCOME 3	INCOME 4
Q5	57.76	54.49	50.27	43.18
Q6	39.86	40.79	40.58	35.54
CCI	-12.31	-6.91	-2.55	6.06
Q9	-9.39	-3.01	0.76	5.93

Figure 16. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory - income.

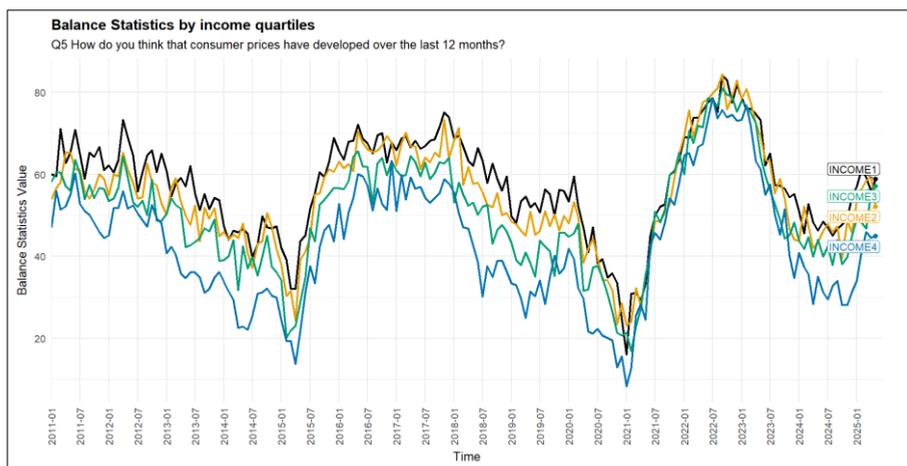


Figure 17. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - income.

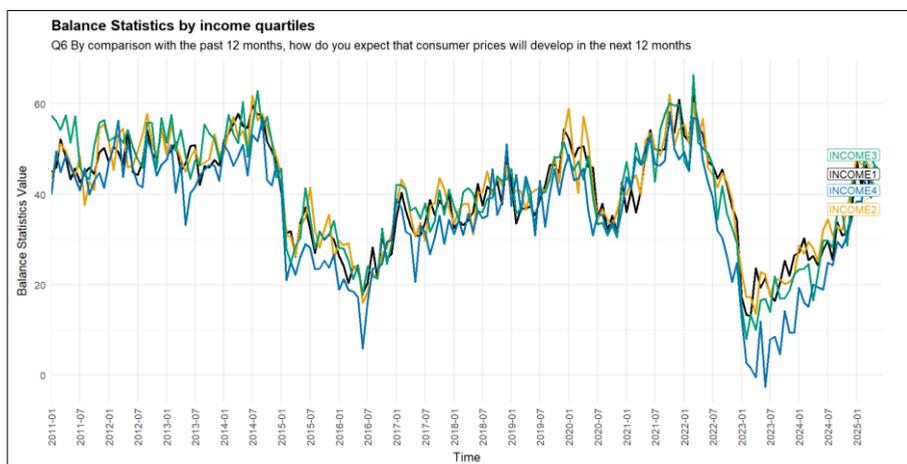


Figure 18. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - income.

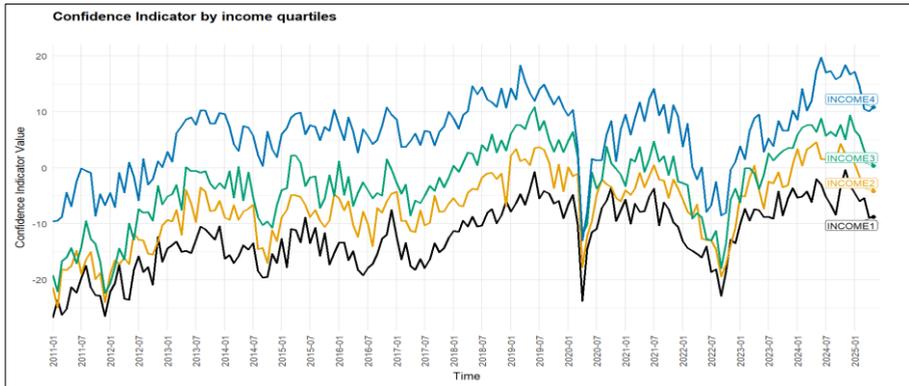


Figure 19. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - income.

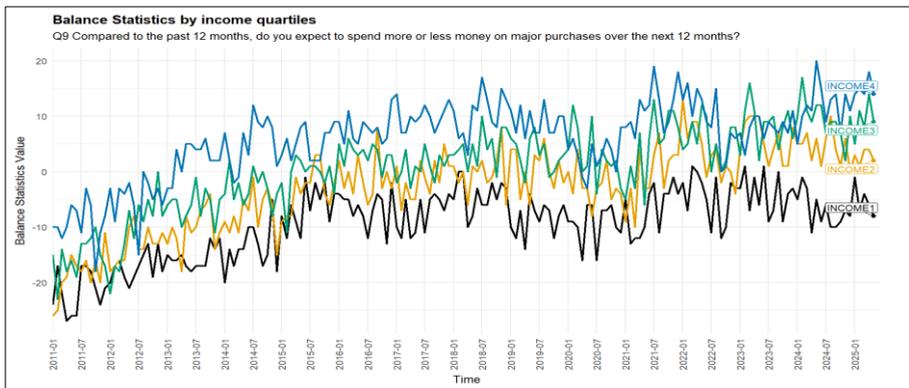


Table 15 presents the balance statistics for education-based subgroups, while Figures 20–23 illustrate their dynamics over time. Results suggest that heterogeneity across education levels is less pronounced than that observed in age or income-based subgroup classifications. Balance statistics of respondents with lower (EDUC1) and intermediate (EDUC2) levels of educational attainment exhibit highly similar dynamics. While minor differences in the mean values of their responses are observable, it appears to be largely contingent on the specific sample period and do not display systematic divergence. Accordingly, these differences are unlikely to be statistically or economically significant. Most notable distinction between these two groups arises in responses to Question 9 (planned durable consumption). Here, the EDUC1 group demonstrates considerably higher variance in their balance statistics, indicating greater volatility in expectations regarding future durable goods expenditure. This may reflect heightened

sensitivity of lower-educated households to short-term economic fluctuations, financial constraints, or greater uncertainty in their consumption planning. Respondents with tertiary education (EDUC3) show somewhat different response patterns. While their inflation expectations (Question 6) do not differ substantially from those of EDUC1 and EDUC2, they tend to report more optimistic assessments on other indicators, such as household finances, economic outlook, and consumer confidence. Nonetheless, these differences are not consistent over time. There are multiple periods in which the balance statistics of EDUC3 responses overlap with those of the lower-educated groups, suggesting that the optimism associated with higher education is not uniformly persistent. Taken together, findings indicate that educational attainment introduces a modest degree of heterogeneity in household survey responses, particularly with respect to durable consumption plans. However, compared to subgroup divisions by age or income, educational differences appear to exert weaker and less systematic influence on inflation perceptions, expectations, and consumer confidence. This suggests that while education shapes aspects of economic outlook, potentially through channels of information processing, financial literacy, or labor market stability, the effect is relatively muted in comparison to demographic and income-related factors.

Table 15. Balance statistics means of Lithuanian households by subcategory - education. Sample period 2011.01-2025.05

	EDUC 1	EDUC 2	EDUC 3
Q5	51.82	54.23	46.67
Q6	36.97	40.20	38.10
CCI	-5.28	-6.10	-0.50
Q9	-5.32	-2.94	2.19

Figure 20. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory – education.

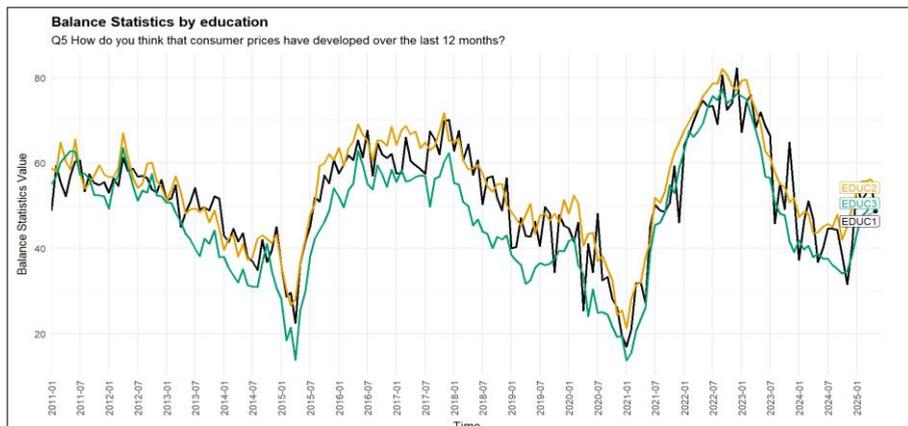


Figure 21. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - education.

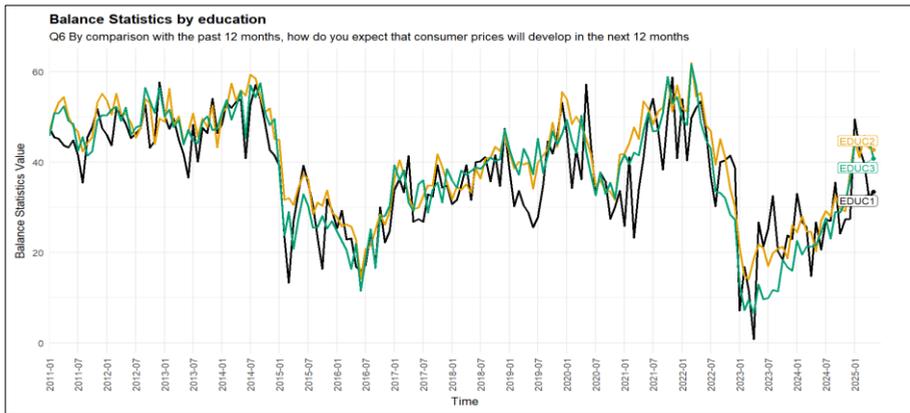


Figure 22. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - education.

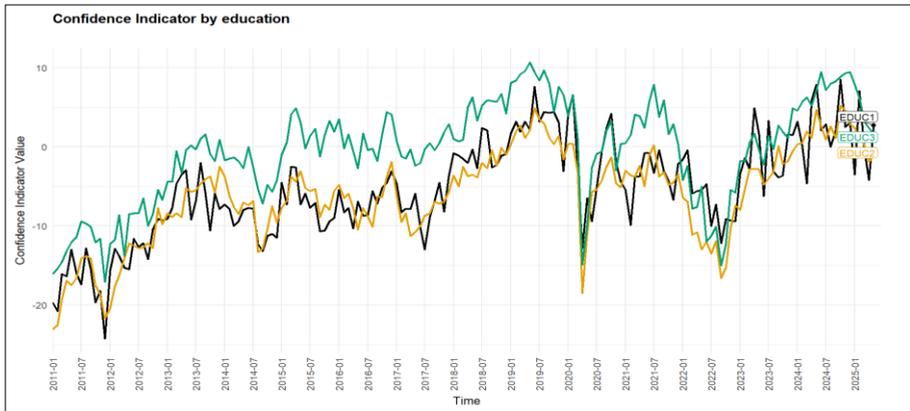


Figure 23. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - education.

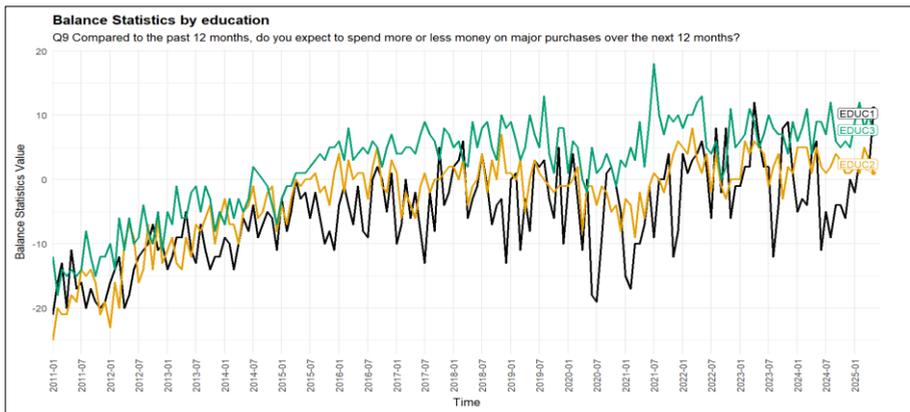


Table 16 reports the balance statistics for sex-based subgroups, while Figures 24–27 depict their evolution over time. Results suggest that gender-related differences in consumer perceptions and expectations are present but comparatively limited in scope. On average, male respondents tend to provide slightly more optimistic assessments than female respondents across most survey questions. However, the magnitude of these differences is small, and in many instances, trajectories of the two groups exhibit considerable overlap. This is particularly evident in Question 6 (inflation expectations) and Question 9 (planned durable consumption), where the response dynamics frequently converge, producing extended periods in which the balance statistics of male and female respondents are virtually indistinguishable. Overall, the analysis indicates that sex-based subgrouping produces the least degree of heterogeneity among all classifications considered (age, income, and education). While marginal differences in optimism levels can be detected, consistent with majority of findings in the literature that female respondents often report more cautious or risk-averse expectations, the practical implications of these differences appear limited. In contrast to the pronounced divergences observed across income or age cohorts, gender-related variation in perceptions of inflation, expectations, and consumer confidence is minor and largely episodic rather than systematic.

Table 16. Balance statistics means of Lithuanian households by subcategory - sex. Sample period 2011.01-2025.05.

	MALE	FEMALE
Q5	47.40	53.66
Q6	37.33	40.27
CCI	-2.19	-4.98
Q9	-0.32	-1.56

Figure 24. Balance statistic dynamics of Lithuanian household responses to question 5 by subcategory – sex.

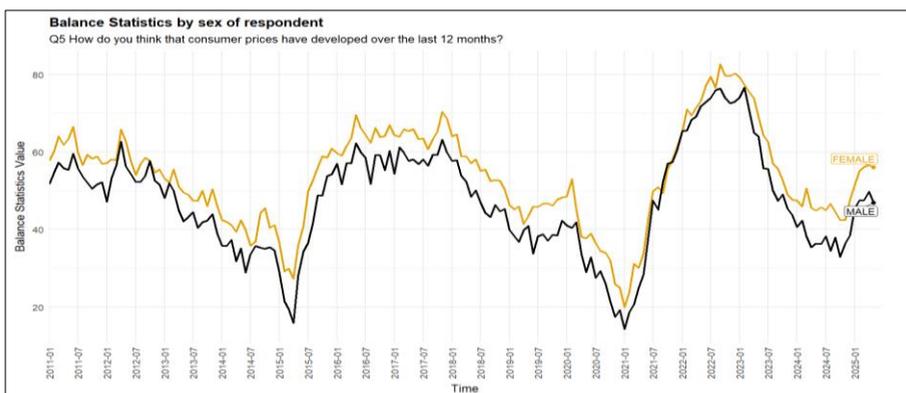


Figure 25. Balance statistic dynamics of Lithuanian household responses to question 6 by subcategory - sex.

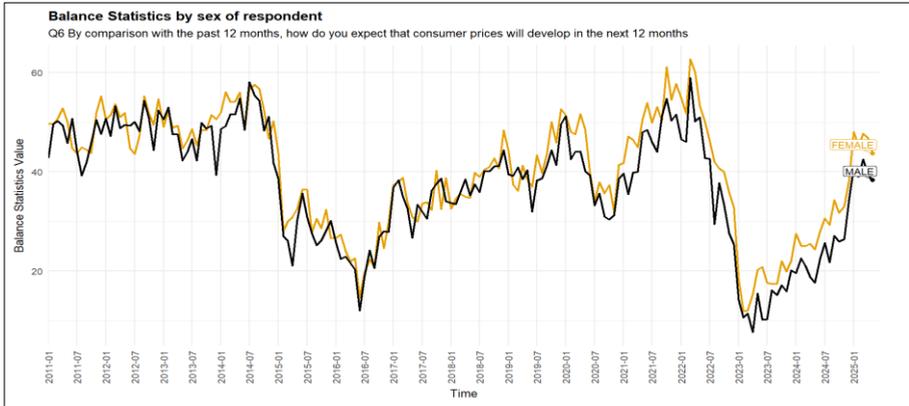


Figure 26. Balance statistic dynamics of Lithuanian household consumer confidence indicator by subcategory - sex.

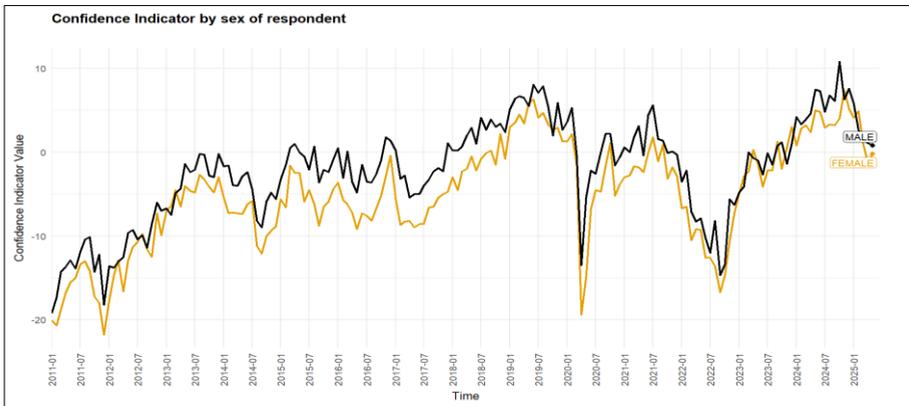
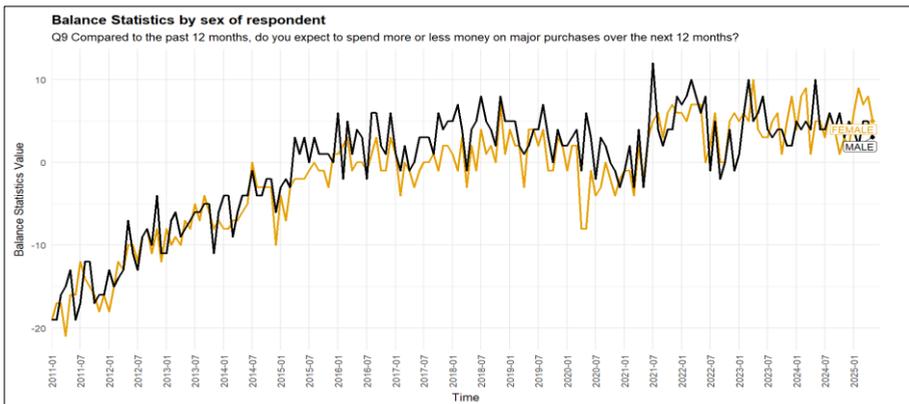


Figure 27. Balance statistic dynamics of Lithuanian household responses to question 9 by subcategory - sex.



It is important to acknowledge the limitations of the dataset when interpreting the results. As data is aggregated at the subgroup level rather than derived from individual-level observations, it is not possible to make causal inferences regarding the determinants of consumer perceptions and expectations. The observed heterogeneity across subgroups may reflect overlapping demographic characteristics rather than the isolated effect of a single factor. For example, the AGE4 cohort (65 years and older) contains a disproportionately higher share of female respondents compared to male respondents. Consequently, differences in response patterns attributed to age may, in fact, be partly driven by underlying gender composition or vice versa. In this sense, subgroup-level analysis captures correlations but does not allow disentangling of potentially confounding influences. Nevertheless, subgroup heterogeneity can still be of use when quantifying consumer responses.

Tables 17-20 present correlations between changes in balance statistics of consumer responses. The most pronounced heterogeneity in the age cohorts appears to be the correlation between Q5 and Q6. It rises steadily from virtually zero for AGE1 (0.037) to 0.272 for AGE4. Older respondents therefore display far greater internal consistency between perceived and expected inflation than the young, whose perceptions and expectations are largely disconnected. While recent research suggests that perceptions of inflation have causal relationship with expectations of price changes, dynamics of younger consumer responses does not appear to follow the same path in Lithuania. Turning to confidence, Q6–CCI correlations are uniformly more negative than Q5–CCI, underscoring the stronger role of inflation expectations than perceptions in shaping consumer confidence. Finally, both Q5 and Q6 show stronger associations with Q9 among younger respondents: Q6–Q9 is -0.202 in AGE1, weakening to nearly zero in AGE4 (-0.001). Similarly, while AGE2 and AGE3 cohorts appear to have a slight positive link between perceived inflation and planned durables consumption (Q5–Q9), the youngest and the oldest cohorts do not share the same dynamics.

Responses disaggregated by income quartiles exhibit a broadly similar, yet distinct correlation structure compared to age cohorts. The correlation between inflation perceptions and expectations (Q5–Q6) is strongest among the lowest-income households (0.233) and the upper-middle quartile (0.223), but considerably weaker for the second (0.103) and highest (0.119) income groups. The underlying reasons for this non-monotonic pattern remain unclear and may reflect heterogeneous information processing, differences in financial constraints, or compositional effects within the quartiles. By contrast, the relationships between perceived or expected inflation and consumer confidence are more uniform across income groups than across age

groups. In all quartiles, higher perceived and expected inflation is associated with lower confidence. However, the strength of this negative association is attenuated among the highest-income households, suggesting that confidence in this group is less sensitive to inflation-related considerations.

Across educational groups, the correlation between inflation perceptions and expectations (Q5–Q6) is relatively stable, with values of 0.246 for respondents with lower educational attainment (EDUC1), 0.265 for those with intermediate education (EDUC2), and a slightly weaker association of 0.209 among the tertiary-educated (EDUC3). In relation to durable consumption plans, the correlation between inflation expectations and durable expenditure (Q6–Q9) becomes progressively more negative with higher education (–0.051 for EDUC1, –0.137 for EDUC2, and –0.149 for EDUC3). This suggests that respondents with higher educational attainment are more likely to incorporate expectations of future inflation into their durable spending decisions. However, the magnitude of differences for different education groups is not large. By contrast, the correlation between inflation perceptions and durable expenditure (Q5–Q9) remains weak across all groups, displaying only a modest positive association among the tertiary-educated (0.075).

Gender-based differences are a bit more pronounced than those observed across educational groups. Among men, the correlation between inflation perceptions and expectations (Q5–Q6) is relatively strong (0.274), whereas for women it is much weaker (0.075). This indicates that male respondents exhibit substantially greater internal consistency between perceived and expected inflation than their female counterparts. The correlation between inflation perceptions and confidence (Q5–CCI) differs not only in magnitude but also in sign: it is slightly positive for women (+0.020) and negative for men (–0.134). This sign reversal constitutes one of the most striking forms of subgroup heterogeneity in the dataset, suggesting that men’s confidence systematically declines with higher inflation perceptions, while women’s confidence does not. The correlation between inflation expectations and durable spending (Q6–Q9) is more negative among men (–0.227) than women (–0.169), though the differences are not that high.

Table 17. Correlation of balance statistic differences between questions. Subcategory - age.

Corr AGE1	Q5	Q6	Q9	CCI	Corr AGE2	Q5	Q6	Q9	CCI
Q5	1	0.037	-0.048	-0.155	Q5	1	0.134	0.107	-0.119
Q6	0.037	1	-0.202	-0.282	Q6	0.134	1	-0.094	-0.268
Q9	-0.048	-0.202	1	0.586	Q9	0.107	-0.094	1	0.37
CCI	-0.155	-0.282	0.586	1	CCI	-0.119	-0.268	0.37	1

Corr AGE3	Q5	Q6	Q9	CCI	Corr AGE4	Q5	Q6	Q9	CCI
Q5	1	0.154	0.132	-0.115	Q5	1	0.272	0.029	-0.053
Q6	0.154	1	-0.067	-0.223	Q6	0.272	1	-0.001	-0.254
Q9	0.132	-0.067	1	0.414	Q9	0.029	-0.001	1	0.535
CCI	-0.115	-0.223	0.414	1	CCI	-0.053	-0.254	0.535	1

Table 18. Correlation of balance statistic differences between questions. Subcategory - income.

Corr INCO ME1	Q5	Q6	Q9	CCI	Corr INCO ME2	Q5	Q6	Q9	CCI
Q5	1	0.233	-0.089	-0.197	Q5	1	0.103	-0.045	-0.143
Q6	0.233	1	0.053	-0.186	Q6	0.103	1	-0.163	-0.381
Q9	-0.089	0.053	1	0.598	Q9	-0.045	-0.163	1	0.371
CCI	-0.197	-0.186	0.598	1	CCI	-0.143	-0.381	0.371	1

Corr INCO ME3	Q5	Q6	Q9	CCI	Corr INCO ME4	Q5	Q6	Q9	CCI
Q5	1	0.223	-0.006	-0.206	Q5	1	0.119	0.005	-0.112
Q6	0.223	1	-0.084	-0.329	Q6	0.119	1	-0.12	-0.196
Q9	-0.006	-0.084	1	0.587	Q9	0.005	-0.12	1	0.569
CCI	-0.206	-0.329	0.587	1	CCI	-0.112	-0.196	0.569	1

Table 19. Correlation of balance statistic differences between questions. Subcategory - education.

Corr EDUC 1	Q5	Q6	Q9	CCI	Corr EDUC 2	Q5	Q6	Q9	CCI
Q5	1	0.246	0.029	-0.115	Q5	1	0.265	-0.004	-0.071
Q6	0.246	1	-0.051	-0.204	Q6	0.265	1	-0.137	-0.342
Q9	0.029	-0.051	1	0.557	Q9	-0.004	-0.137	1	0.531
CCI	-0.115	-0.204	0.557	1	CCI	-0.071	-0.342	0.531	1

Corr EDUC 3	Q5	Q6	Q9	CCI
Q5	1	0.209	0.075	-0.105
Q6	0.209	1	-0.149	-0.331
Q9	0.075	-0.149	1	0.5
CCI	-0.105	-0.331	0.5	1

Table 20. Correlation of balance statistic differences between questions. Subcategory - sex.

Corr MALE	Q5	Q6	Q9	CCI	Corr FEMALE	Q5	Q6	Q9	CCI
Q5	1	0.274	0.023	-0.134	Q5	1	0.075	0.094	0.02
Q6	0.274	1	-0.227	-0.294	Q6	0.075	1	-0.169	-0.346
Q9	0.023	-0.227	1	0.489	Q9	0.094	-0.169	1	0.509
CCI	-0.134	-0.294	0.489	1	CCI	0.02	-0.346	0.509	1

5.2. Carlson-Parkin Method on Subcategory Data

The presence of heterogeneity in household survey responses opens the possibility of adopting a novel approach to the application of the Carlson–Parkin probability method for quantifying consumer inflation perceptions and expectations. Prior research has consistently documented that households exhibit an upward bias in both their perceived and expected inflation, with Lithuanian consumers ranking among the most pessimistic in the European Union. Building on these insights, this study proposes the use of subgroup-level data to refine the quantification procedure. Specifically, the subgroup

with the lowest balance statistic is treated as a reference point, quantified under the assumption of a normal distribution. In contrast, the remaining subgroups are quantified using a non-central t-distribution, with the non-centrality parameter defined in the below equation. Once the inflation perceptions or expectations of all subgroups have been quantified, the results are subsequently aggregated using population-based weights. Specifically, the relative share of each subgroup in the overall population, for example, the percentage of individuals belonging to a given age cohort, is employed as the aggregation weight for the corresponding subgroup.

$$ncp = \frac{BS_1 - BS_2}{SE_{(BS_1 - BS_2)}} \quad (20)$$

Where, BS_1 denotes the balance statistic of the comparatively more pessimistic subgroup (/100), while BS_2 refers to the balance statistic of the reference subgroup (/100).

Since the analysis considers four subgroup classifications: age, income, education, and sex, four distinct sets of aggregate measures will be obtained. In the final step, these subgroup-adjusted aggregates will be benchmarked against the canonical application of the Carlson–Parkin method, which applies the normal distribution directly to the aggregate survey responses. The relative accuracy of the two approaches will be evaluated by comparing their RMSE values. The scaling parameter in the quantification process will be actual YoY inflation rate, π_{t-13} , for perceptions and, π_{t-1} , for expectations. Given that heterogeneity is more pronounced in Lithuanian consumers’ perceptions of inflation, the proposed approach is first applied to the quantification of Q5 responses. For inflation expectations (Q6), the method is instead implemented using euro area data, where heterogeneity across subgroups is more substantial and thus provides a more suitable testing ground for the framework.

5.3. Results of Subgroup Data Quantification

The accuracy of the proposed quantification procedure is assessed by comparing the root mean squared error (RMSE) of subgroup-adjusted measures with that of the canonical Carlson–Parkin (CP) method applied directly to aggregate responses. Table 21 reports the results for Lithuanian consumers’ perceptions of inflation (Q5), covering both the full sample period (January 2011–May 2025) and the pre-pandemic subsample (January 2011–December 2019). For the full sample, all four subgroup-based approaches yield substantial improvements in accuracy relative to the canonical method.

The largest accuracy gains are observed when disaggregating by income, where the RMSE ratio is 1.367, suggesting 36.7% accuracy gains when compared to canonical CP approach. A nearly identical result is obtained for age-based disaggregation. Disaggregation by education and sex also improves accuracy, though somewhat less strongly, with RMSE ratios of 1.282 and 1.231, respectively. These findings suggest that subgroup heterogeneity, particularly by income and age, is highly relevant for perceptions of inflation in Lithuania and aggregating quantified subgroup perceptions can offer significant accuracy gains. Restricting the analysis to the pre-pandemic period for robustness of the results yields qualitatively similar, though less pronounced, improvements. In this subsample, the canonical CP method produces an RMSE of 1.749, while subgroup-based approaches reduce this to between 1.471 and 1.529. The strongest accuracy gains arise from income-based categorization (ratio - 1.189), the same as with the full sample. The gains are similar though when considering age (1.179) and education (1.173) subgroupings. Even when the overall level of error is lower, as is the case before the inflation surge of 2021–2022, recognizing subgroup heterogeneity continues to yield consistent efficiency gains.

Taken together, these results demonstrate the practical value of the proposed methodology. By first quantifying inflation perceptions at the subgroup level and subsequently aggregating the results with population weights, the approach systematically improves accuracy relative to the standard aggregate CP method.

Table 21. Accuracy of quantified Lithuanian consumer inflation perceptions.

LT Q5	CP on aggregate data	Aggregate of age subgroups	Aggregate of income subgroups	Aggregate of education subgroups	Aggregate of sex subgroups
Sample 2011.01-2025.05					
RMSE value	6.779	4.965	4.959	5.287	5.505
RMSE ratio	-	1.365	1.367	1.282	1.231
Sample 2011.01-2019.12					
RMSE value	1.749	1.483	1.471	1.491	1.529
RMSE ratio	-	1.179	1.189	1.173	1.144

Due to low heterogeneity of household responses to question 6 in Lithuania, the procedure is further evaluated for euro area households' inflation expectations. The results are also obtained for two periods for

robustness and are presented in Table 22. For the full sample, all subgroup classifications deliver clear accuracy gains over the canonical approach. Age based subcategory approach yields accuracy improvement of around 14.5%. The gains are larger when disaggregating by other categories and are rather comparable - income category yields RMSE ratio of 1.217, education - 1.233 and sex-based subgrouping – 1.248. These results confirm that accounting for subgroup heterogeneity yields systematic improvements in quantifying inflation expectations across the euro area. The pre-pandemic subsample reveals a more nuanced pattern. In this lower-volatility environment, age-based disaggregation fails to improve accuracy, with an RMSE ratio below unity (0.981). By contrast, all other subgroupings outperform the canonical method. The strongest gains again arise from disaggregation by education (ratio - 1.290) and sex (ratio - 1.284), followed by income (ratio - 1.131). These results suggest that even in relatively stable periods, certain subgroup dimensions, particularly education and gender, can provide meaningful improvements in the mapping from qualitative survey responses to quantitative measures of inflation expectations.

Overall, the evidence demonstrates that the proposed subgroup-adjusted approach consistently enhances the accuracy of quantified inflation expectations relative to the canonical CP method. The magnitude of the gains is especially pronounced when heterogeneity is most salient, as in the case of education and gender, but remains positive across nearly all subgroup dimensions. These findings show that applying CP method on subgroup-level data allowing adjustment to upward bias constitutes a possible methodological advancement with empirical benefits in accuracy.

Table 22. Accuracy of quantified euro area consumer inflation expectations.

EA Q6	CP on aggregate data	Aggregate of age subgroups	Aggregate of income subgroups	Aggregate of education subgroups	Aggregate of sex subgroups
Sample 2011.01-2025.05					
RMSE value	2.901	2.534	2.384	2.353	2.324
RMSE ratio	-	1.145	1.217	1.233	1.248
Sample 2011.01-2019.12					
RMSE value	0.994	1.013	0.879	0.770	0.774
RMSE ratio	-	0.981	1.131	1.290	1.284

5.4. Concluding Remarks

This study has demonstrated that accounting for subgroup heterogeneity provides meaningful improvements in the quantification of consumer inflation perceptions and expectations. Using Lithuanian household survey data, the application of the Carlson–Parkin method at the subgroup level followed by population-weighted aggregation was shown to reduce RMSE substantially compared to the canonical aggregate approach.

The gains were particularly pronounced when disaggregating by income and age, highlighting the importance of demographic and socio-economic variation in shaping inflation perceptions. Extending the analysis to the euro area, where heterogeneity in expectations is more evident, confirmed the robustness of the findings. Here, disaggregation by education and gender produced the largest accuracy gains, demonstrating that subgroup-based quantification enhances measurement even in more stable inflation environments. The benefits of subgroup-based quantification extend beyond the reduction in RMSE. Applying the CP method separately across demographic groups retains variation that is otherwise lost in the aggregate series, and this added granularity is useful from a policy communication perspective. Although the method does not identify the sources or behavioral mechanisms behind such variation, the improvement in accuracy indicates that aggregation obscures structure in the data that may be relevant for understanding how expectations align with inflation developments.

As a result, subgroup-based measures offer policymakers a clearer indication of where aggregate indicators may be less informative and where communication efforts might require more differentiation across population segments. Despite these results, several limitations warrant consideration; however, none of them invalidate the core finding that accounting for subgroup heterogeneity materially improves the quantification of consumer inflation perceptions and expectations. First, the analysis relies on balance statistics aggregated at the subgroup level, which limits the ability to isolate overlapping demographic effects. Nonetheless, using balance statistics remains consistent with the data structure available across countries and ensures comparability with the wider CP-method literature. Second, subgroup definitions are static and may not fully capture intra-group mobility over time, particularly for income quartiles. While this may attenuate some of the heterogeneity captured, it biases the results against finding gains from disaggregation, meaning the improvements documented here are likely a lower bound rather than an overstatement. Third, although the framework is applied to Lithuania and the euro area, its ability to improve forecasting or to

generalize to other country cases remains to be tested. This limitation points to a natural next step rather than a weakness of the current approach: the method is readily extendable to other survey systems, and its performance in predictive settings constitutes a promising avenue for further research.

CONCLUSIONS

The motivation for this dissertation stems from a simple but persistent problem in economics: while inflation expectations are central to theory and policy, their measurement and interpretation remain highly contested. My work has approached this problem from both a methodological and an empirical perspective. It has considered how expectations are formed, how they can be quantified, and what role they play in the dynamics of inflation, particularly in the context of the Baltic states and the European Union. The focus on the Baltic states and the European Union is motivated by both substantive and methodological considerations. The Baltics exhibit inflation dynamics that differ markedly from those in the broader euro area: their average inflation and volatility have been persistently higher, and consumer balance statistics show systematically weaker alignment with realized inflation than in the euro area aggregates. These features suggest that households may form expectations under conditions of greater uncertainty, asymmetry, and salience, making the region a demanding environment in which to evaluate the robustness of the Carlson–Parkin framework. At the same time, situating the Baltic evidence within the wider EU context enables a direct comparison with economies where inflation expectations tend to be more stable and where the CP method has traditionally been applied. This dual focus therefore provides a meaningful test of whether commonly used quantification approaches remain consistent across heterogeneous economic environments and whether country-specific structural features materially affect expectation formation.

Taken together, the results from the methodological analysis, the Baltic-country evidence, and the European panel analysis point to a set of common findings. For clarity, these main findings are summarized below:

1. While Carlson–Parkin method remains influential, its conventional assumptions, especially the normal distribution of expectations and symmetric indifference intervals, have been increasingly questioned. At the same time, new developments such as the ECB Consumer Expectations Survey and experimental designs using randomized controlled trials are expanding the ways in which we can study expectations. This methodological context provided the rationale for the empirical strategies I pursued.
2. Relaxing the normality assumption of the Carlson–Parkin framework can improve the quantification of consumer inflation expectations. Using data from Lithuania, Latvia, and Estonia, I compared the fit and predictive accuracy of alternative distributions. The results

showed that while non-normal distributions can better capture skewness or kurtosis in the data, the gains in predictive performance were modest in majority of samples considered. These findings highlight both the value and the limits of methodological refinement. Quantification techniques can improve the robustness of survey-based measures, but they cannot fully overcome the inherent biases and volatility in consumer expectations. The analysis also showed that the choice of scaling parameter exerted a stronger influence on accuracy than the choice of distribution, underlining the methodological sensitivity of quantified expectations. This observation aligns with the broader literature on expectation formation, which stresses behavioral factors, salience, and limited information rather than purely statistical shortcomings.

3. Inflation expectations in the Baltics are more volatile and less closely aligned with realized inflation than in euro area. These findings reflect that expectations are shaped by national context, and that a uniform approach to measurement across countries risks obscuring important differences. Regarding forward-lookingness, consumers in the Baltics appeared to form expectations over shorter horizons (around 6–8 months) rather than the standard 12-month period. What is more, examining the predictive power of quantified expectations showed that it rarely improved inflation forecasting when compared to the use of simple balance statistics.
4. Consumer expectations do not appear as dominant sources of variation in inflation dynamics. Instead, supply-side shocks and realized inflation explain most of the observed dynamics. Wage–price spirals, often feared in theory, appeared limited in practice. Nonetheless, expectations did show relevance in influencing short-term consumption and in reflecting household sentiment. These findings contribute to the ongoing debate sparked by Rudd (2021), who question the centrality of expectations in modern models. My results suggest that while expectations matter, their role is more nuanced, conditional, and context-dependent than traditional theory assumes. Finally, the robustness checks demonstrated that results were sensitive to the quantification method used, underlining the importance of methodological choices when modelling expectations, namely, the choice of distributional assumptions and scaling parameters, produced non-trivial differences in impulse responses. In some cases, using perceived rather than actual inflation as the scaling factor amplified the estimated effect of expectations on consumption

and inflation. The dynamics and role of consumer sentiment was also affected. What is more, the study highlighted significant heterogeneity across individual countries.

5. Analyzing subgroup data disaggregated by age, income, education, and gender reveals heterogeneity of consumer inflation expectations. The results demonstrated that applying the Carlson–Parkin method at the subgroup level and subsequently aggregating with population weights consistently improves accuracy compared to the canonical aggregate approach. For Lithuania, the largest gains were observed when disaggregating by income and age, yielding accuracy improvements of more than 30 percent relative to the standard method. Extending the framework to euro area data confirmed these results, with particularly strong gains when accounting for education and gender heterogeneity. The analysis also highlighted distinct subgroup patterns: younger households and lower-income respondents systematically reported lower inflation perceptions, while older cohorts displayed greater internal consistency between perceived and expected inflation. Overall, recognizing and incorporating subgroup heterogeneity provides not only more accurate quantification of expectations but also richer insights into the socio-demographic factors that shape household perceptions of inflation.

In addition to its empirical findings, the dissertation makes several methodological contributions to the measurement and analysis of consumer inflation expectations:

- By comparing alternative Carlson–Parkin specifications and balance statistics within the same panel VAR model, the dissertation demonstrates that methodological choices made at the quantification stage materially affect estimated impulse responses and variance decompositions. This approach links the technical details of expectation measurement directly to macroeconomic inference, showing that conclusions about the role of expectations in inflation and consumption dynamics are sensitive to how qualitative survey data are transformed into quantitative indicators.

- Development and evaluation of a subgroup-based quantification approach to consumer inflation expectations. Instead of applying the Carlson–Parkin method to aggregate survey data, the dissertation quantifies expectations separately for socio-demographic subgroups and subsequently aggregates them using population weights. This procedure is shown to consistently improve accuracy relative to the canonical aggregate approach

and to yield richer insights into expectation formation across age, income, education, and gender groups. The results demonstrate that heterogeneity is not merely a descriptive feature of expectations, but a dimension that can be explicitly incorporated into the measurement process itself.

Taken together, the contributions of the dissertation are threefold. First, it provides a critical assessment of the Carlson–Parkin method and its alternatives, showing both the possibilities and the limits of methodological refinements. Second, it extends empirical evidence to the Baltic states and offers a detailed account of how expectations behave in these under-researched economies, including the role of euro adoption. Third, it contributes to the wider European debate by demonstrating, through panel analysis, that consumer expectations have only limited predictive power for inflation but remain relevant indicators of household sentiment and consumption dynamics. The implications of these findings are both theoretical and practical. On the theoretical side, the evidence supports models of bounded rationality and limited attention. It challenges the idea that consumers form unbiased, forward-looking expectations, and strengthens the case for incorporating behavioral mechanisms into macroeconomic frameworks. On the policy side, the results highlight the importance of central bank communication and credibility. If consumer expectations are volatile, biased, and heterogeneous, then managing them depends less on the precise technicalities of survey quantification and more on effective targeted communication strategies.

Like any empirical investigation, this dissertation is subject to several limitations that should be acknowledged. Although this dissertation explored alternatives to normal distribution assumption in application of Carlson–Parkin method, the improvements in accuracy were modest. This suggests that the scope for purely statistical refinements is constrained. Moreover, the analysis demonstrated that results of modelling are sensitive to the choice of scaling parameters, distributional assumptions, and aggregation procedures. While robustness checks were undertaken, the dependence on such modelling decisions implies that the findings should be interpreted with caution. Different methodological choices may yield quantitatively different outcomes, even if the qualitative conclusions remain broadly consistent. The scope of the empirical analysis also imposes constraints. Much of the dissertation focused on the Baltic states, which, although of interest, are small economies with idiosyncratic characteristics. Finally, the temporal dimension of the study deserves mention. The data cover a period that includes both moderate inflation years and the more recent high-inflation surge. While this

provides an opportunity to test expectations in very different environments, it also means that the conclusions are tied to the dynamics of these episodes.

Future research could build on the present analysis in several important directions. First, extending the empirical framework to longer historical samples would allow for an assessment of the stability of the results across different inflation regimes and macroeconomic environments, including periods of persistently low inflation and episodes of heightened inflationary pressure. Second, further work could investigate the underlying sources of heterogeneity in consumer responses, distinguishing between demographic, socioeconomic, and informational factors, as well as examining whether the structure and drivers of heterogeneity differ systematically across countries. Third, future work could evaluate the real-time performance of subgroup-based inflation expectation indicators and their usefulness for monetary policy analysis compared with aggregate measures. Finally, future research could examine the effective forecast horizon underlying consumer inflation expectations, exploring whether respondents indeed form expectations over a 12-month horizon or whether their responses reflect shorter or variable horizons, and how such horizon heterogeneity affects the interpretation of survey-based expectation measures.

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ANNEX A

Table 23. RMSE values using actual YoY inflation (π_t) as a scaling parameter.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Normal	4.346	4.774	4.653	2.445	1.842
Logistic	4.360	4.814	4.684	2.465	1.844
Central t	4.360	4.835	4.685	2.487	1.838
Non-central t	4.350	4.629	4.643	2.722	1.942
Non-central t 2	4.362	4.839	4.688	2.489	1.839
Sample 2001.05-2019.12					
Normal	3.100	3.609	3.130	1.745	1.143
Logistic	3.112	3.671	3.160	1.757	1.142
Central t	3.099	3.712	3.177	1.770	1.138
Non-central t	2.913	3.471	3.007	1.749	1.156
Non-central t 2	3.102	3.720	3.180	1.771	1.139
Sample 2012.01-2019.12					
Normal	1.724	1.410	1.670	1.324	0.771
Logistic	1.728	1.443	1.663	1.341	0.776
Central t	1.723	1.452	1.658	1.357	0.778
Non-central t	1.546	1.363	1.598	1.296	0.771
Non-central t 2	1.723	1.450	1.659	1.359	0.779
Sample 2020.01-2023.07					
Normal	8.026	8.410	8.935	4.512	3.692
Logistic	8.049	8.411	8.976	4.556	3.699
Central t	8.073	8.394	8.953	4.599	3.689
Non-central t	8.459	8.628	9.181	5.929	3.993
Non-central t 2	8.072	8.389	8.951	4.598	3.689
Sample pre euro adoption					
Normal	1.754	2.478	3.211	-	-
Logistic	1.730	2.679	3.396	-	-
Central t	1.707	2.696	3.394	-	-
Non-central t	1.081	2.482	3.364	-	-
Non-central t 2	1.706	2.691	3.392	-	-
Sample post euro adoption					
Normal	2.053	0.749	3.146	-	-
Logistic	2.071	0.769	3.269	-	-
Central t	2.064	0.773	3.267	-	-
Non-central t	2.123	0.748	3.580	-	-
Non-central t 2	2.065	0.773	3.265	-	-

Table 24. RMSE values using actual lagged YoY inflation (π_{t-1}) as a scaling parameter.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Normal	4.244	4.576	4.448	2.404	1.806
Logistic	4.265	4.636	4.497	2.431	1.811
Central t	4.270	4.673	4.513	2.459	1.808
Non-central t	4.306	4.482	4.528	2.709	1.923
Non-central t 2	4.274	4.679	4.518	2.461	1.809
Sample 2001.05-2019.12					
Normal	3.055	3.449	3.006	1.718	1.129
Logistic	3.072	3.528	3.047	1.733	1.129
Central t	3.061	3.580	3.071	1.752	1.124
Non-central t	2.860	3.315	2.904	1.728	1.143
Non-central t 2	3.066	3.589	3.075	1.753	1.125
Sample 2012.01-2019.12					
Normal	1.723	1.411	1.637	1.308	0.772
Logistic	1.728	1.444	1.631	1.327	0.777
Central t	1.723	1.453	1.626	1.347	0.778
Non-central t	1.544	1.372	1.574	1.293	0.779
Non-central t 2	1.723	1.453	1.626	1.348	0.779
Sample 2020.01-2023.07					
Normal	7.773	8.069	8.503	4.426	3.599
Logistic	7.808	8.105	8.583	4.483	3.616
Central t	7.843	8.117	8.590	4.537	3.613
Non-central t	8.395	8.465	8.946	5.919	3.956
Non-central t 2	7.839	8.108	8.583	4.534	3.611
Sample pre euro adoption					
Normal	1.750	2.432	3.091	-	-
Logistic	1.728	2.667	3.224	-	-
Central t	1.707	2.684	3.220	-	-
Non-central t	1.099	2.479	3.028	-	-
Non-central t 2	1.707	2.679	3.217	-	-
Sample post euro adoption					
Normal	2.001	0.729	3.354	-	-
Logistic	2.020	0.751	3.557	-	-
Central t	2.014	0.757	3.555	-	-
Non-central t	2.064	0.722	3.829	-	-
Non-central t 2	2.015	0.757	3.553	-	-

Table 25. RMSE values using quantified perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Normal	5.184	5.383	5.472	3.104	2.313
Logistic	5.216	5.458	5.590	3.130	2.329
Central t	5.224	5.488	5.600	3.155	2.327
Non-central t	5.128	5.294	5.490	3.316	2.387
Non-central t 2	5.228	5.493	5.603	3.156	2.327
Sample 2001.05-2019.12					
Normal	3.405	3.643	3.376	2.225	1.221
Logistic	3.450	3.714	3.428	2.241	1.223
Central t	3.459	3.766	3.458	2.257	1.218
Non-central t	3.109	3.384	3.247	2.189	1.290
Non-central t 2	3.465	3.775	3.462	2.258	1.218
Sample 2012.01-2019.12					
Normal	2.595	1.817	2.813	1.647	0.743
Logistic	2.643	1.915	2.864	1.682	0.746
Central t	2.630	1.920	2.882	1.716	0.745
Non-central t	2.299	1.839	2.463	1.631	0.794
Non-central t 2	2.633	1.923	2.887	1.718	0.746
Sample 2020.01-2023.07					
Normal	10.073	10.280	10.978	5.702	4.920
Logistic	10.098	10.387	11.245	5.754	4.960
Central t	10.106	10.389	11.232	5.802	4.961
Non-central t	10.346	10.449	11.219	6.871	5.060
Non-central t 2	10.106	10.390	11.233	5.799	4.961
Sample pre euro adoption					
Normal	3.048	2.628	2.928	-	-
Logistic	3.079	2.784	2.923	-	-
Central t	3.056	2.796	2.922	-	-
Non-central t	2.273	2.789	3.421	-	-
Non-central t 2	3.061	2.790	2.918	-	-
Sample post euro adoption					
Normal	2.534	1.009	4.236	-	-
Logistic	2.620	1.019	4.414	-	-
Central t	2.607	1.028	4.404	-	-
Non-central t	2.506	0.935	4.643	-	-
Non-central t 2	2.607	1.027	4.404	-	-

Table 26. RMSE values using quantified perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, running average is used as a scaling parameter.

	LT	LV	EE	PL	EA
Sample 2001.05-2023.07					
Normal	4.731	4.837	4.722	3.198	2.009
Logistic	4.745	4.877	4.733	3.212	2.003
Central t	4.758	4.919	4.746	3.226	1.999
Non-central t	4.967	4.924	4.864	3.428	2.135
Non-central t 2	4.760	4.923	4.750	3.227	2.000
Sample 2001.05-2019.12					
Normal	3.187	3.557	2.861	1.700	1.059
Logistic	3.196	3.616	2.878	1.703	1.050
Central t	3.205	3.678	2.903	1.709	1.041
Non-central t	3.225	3.482	2.842	1.785	1.157
Non-central t 2	3.207	3.682	2.906	1.710	1.041
Sample 2012.01-2019.12					
Normal	2.308	1.702	2.319	1.621	0.422
Logistic	2.279	1.709	2.352	1.644	0.416
Central t	2.250	1.715	2.392	1.680	0.413
Non-central t	1.896	1.599	1.901	1.572	0.585
Non-central t 2	2.252	1.716	2.394	1.682	0.415
Sample 2020.01-2023.07					
Normal	9.553	9.850	10.659	5.918	3.479
Logistic	9.575	9.860	10.670	5.971	3.465
Central t	9.596	9.870	10.677	6.019	3.453
Non-central t	10.059	10.087	10.856	7.089	3.985
Non-central t 2	9.594	9.867	10.674	6.016	3.453
Sample pre euro adoption					
Normal	2.827	2.555	4.258	-	-
Logistic	2.797	2.697	4.182	-	-
Central t	2.769	2.699	4.182	-	-
Non-central t	1.640	2.719	4.278	-	-
Non-central t 2	2.771	2.698	4.182	-	-
Sample post euro adoption					
Normal	2.278	0.691	1.963	-	-
Logistic	2.295	0.691	1.962	-	-
Central t	2.294	0.691	1.961	-	-
Non-central t	2.290	0.694	2.451	-	-
Non-central t 2	2.294	0.691	1.962	-	-

Figure 28. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.

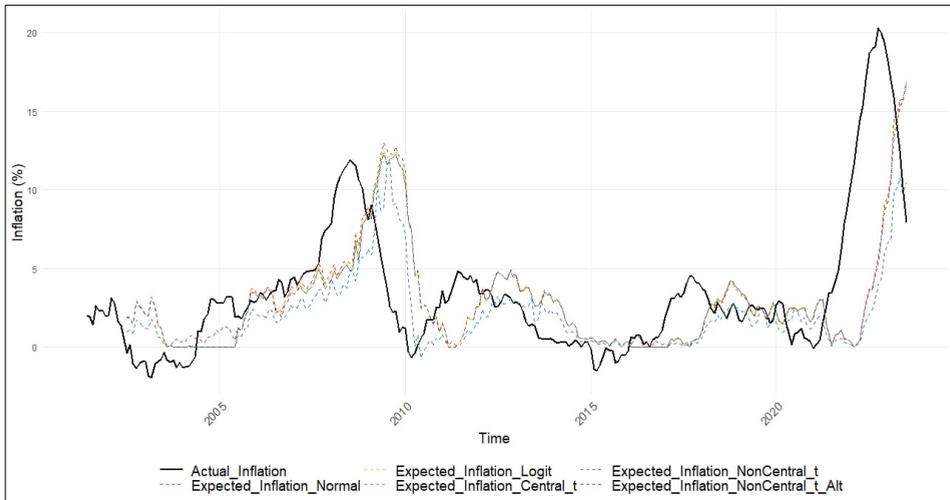


Figure 29. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.

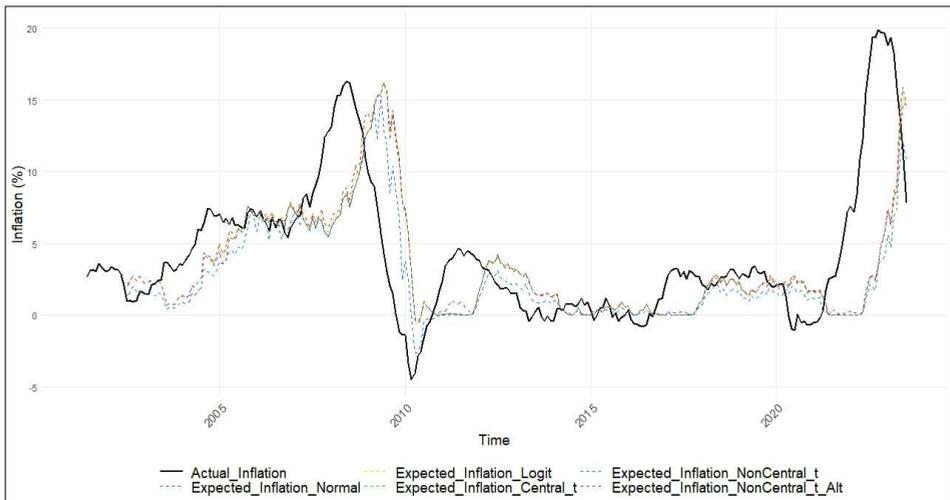


Figure 30. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.

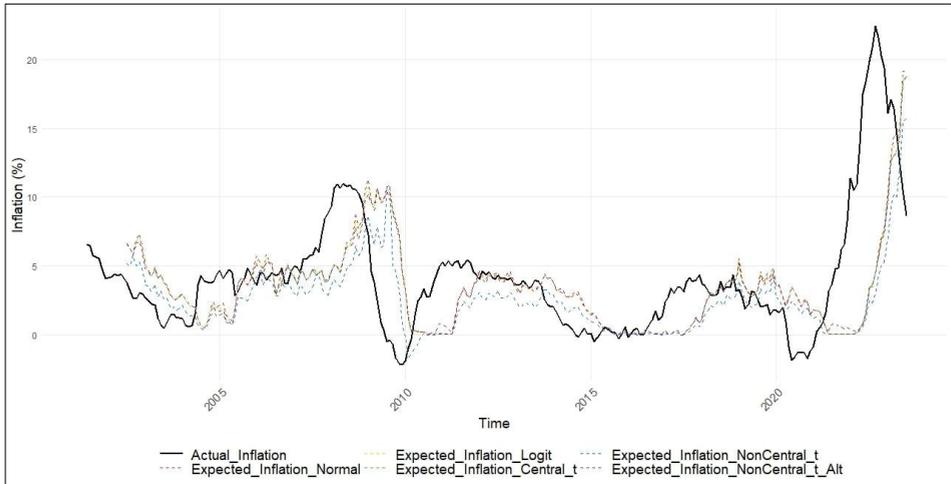


Figure 31. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.

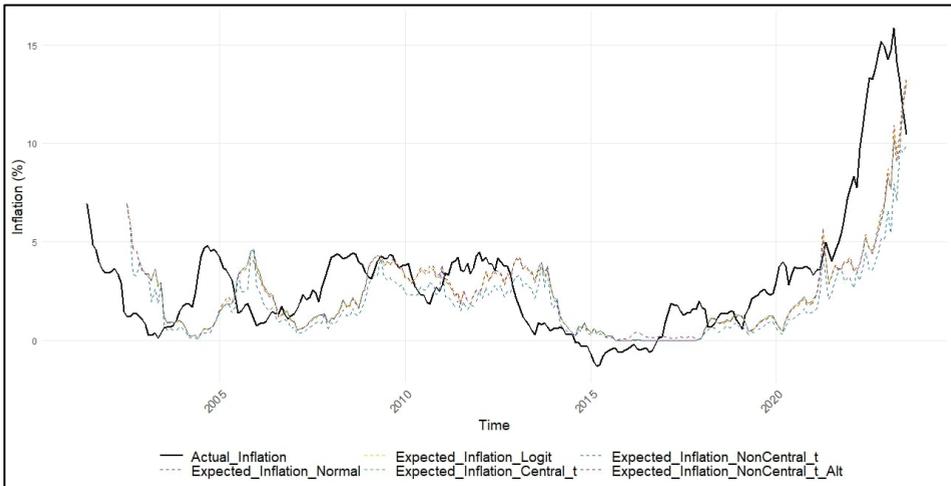


Figure 32. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using lagged actual YoY inflation (π_{t-1}) as a scaling parameter.

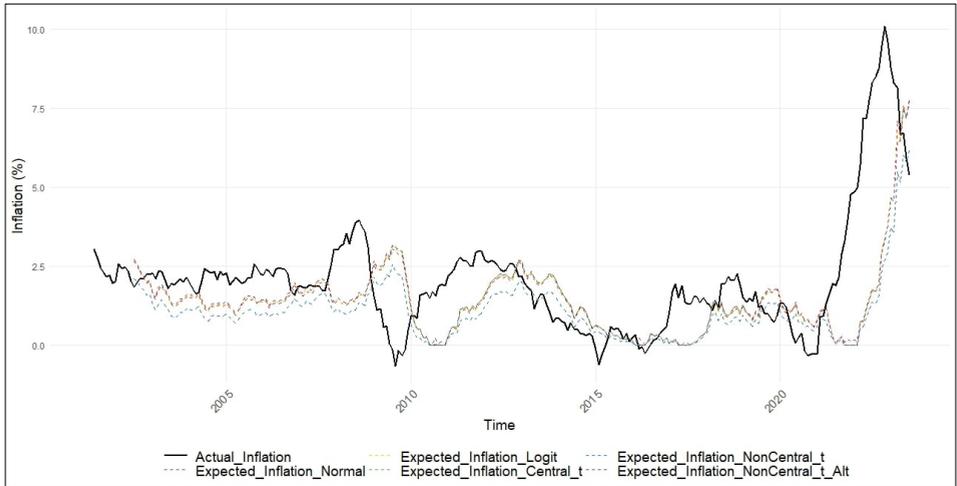


Figure 33. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).

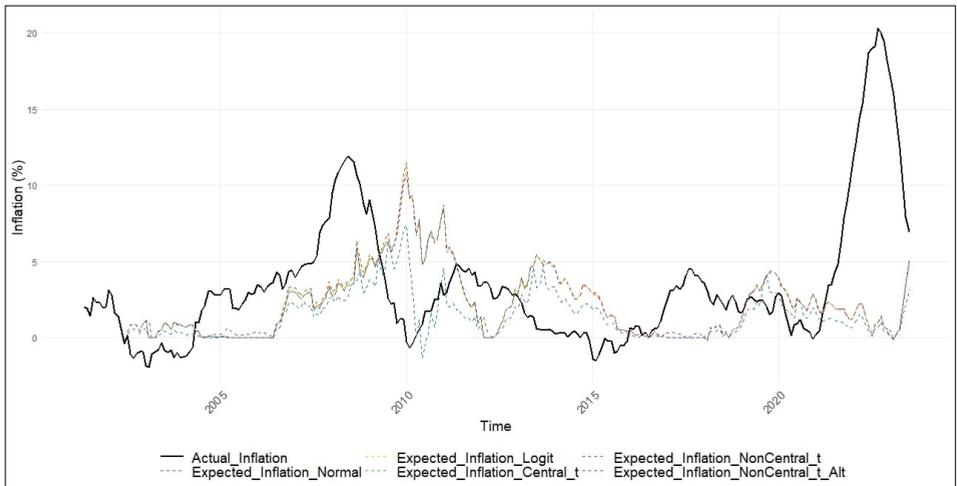


Figure 34. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).

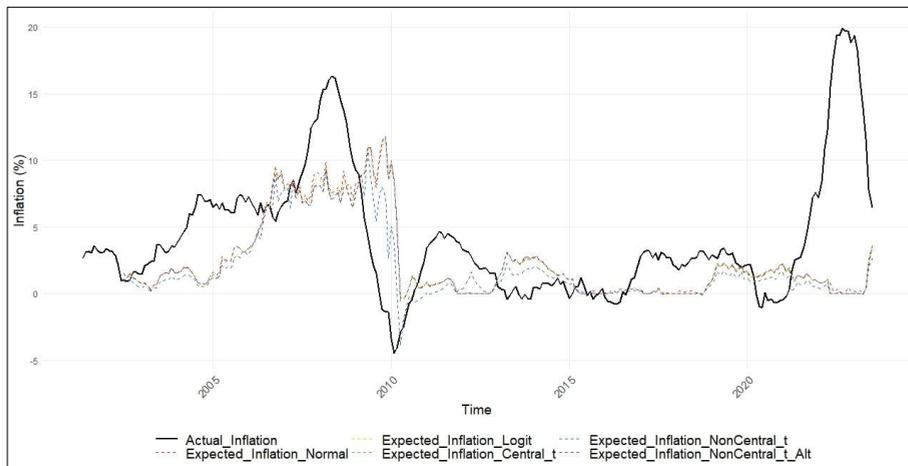


Figure 35. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).

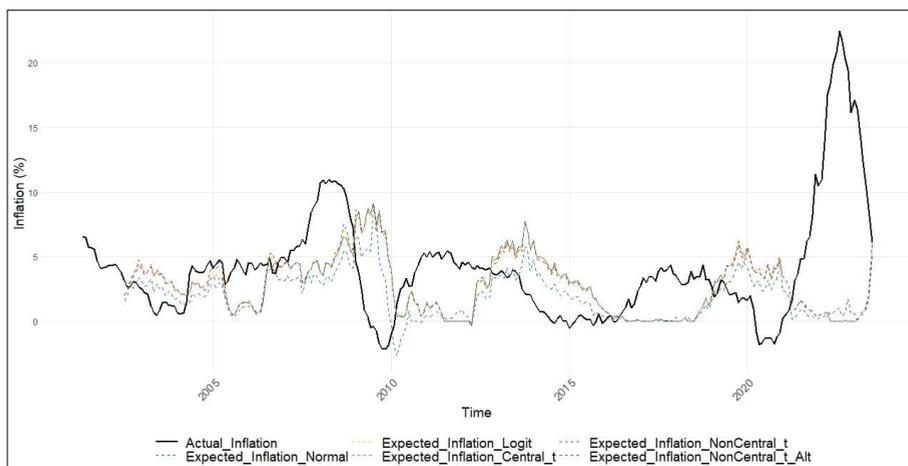


Figure 36. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).

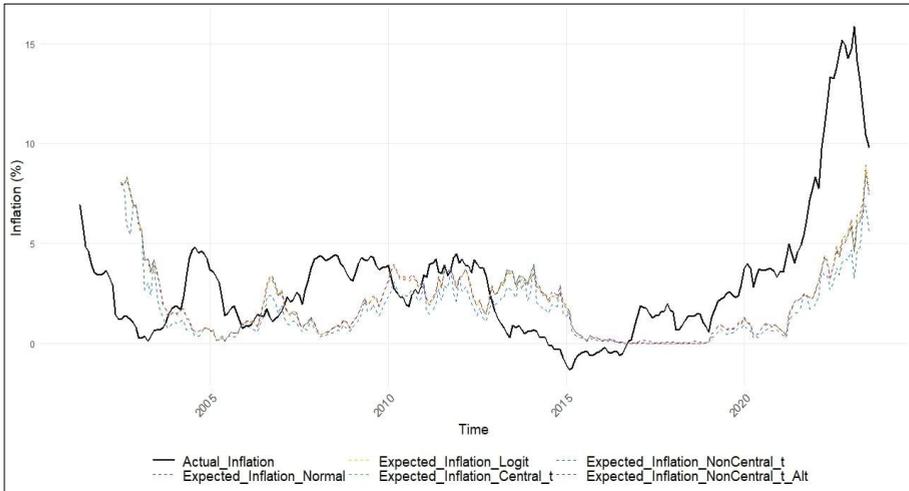


Figure 37. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, actual inflation is used as scaling parameter (π_{t-12}).

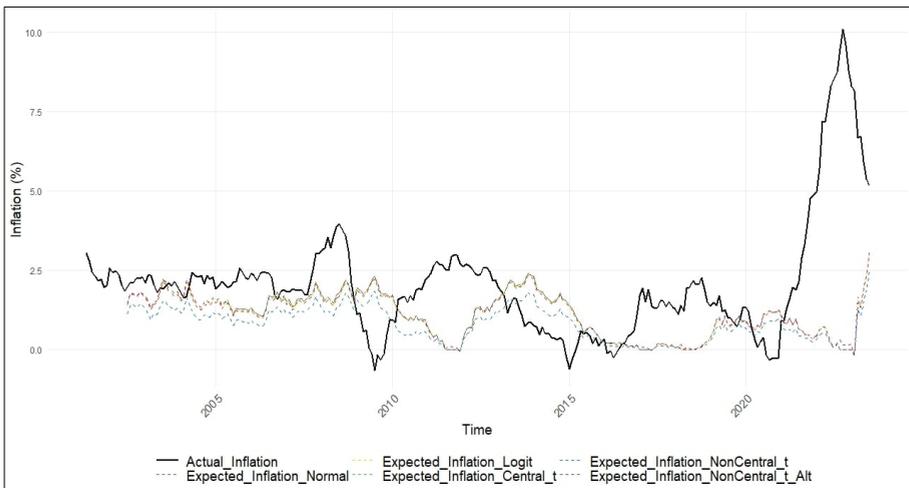


Figure 38. Lithuanian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.

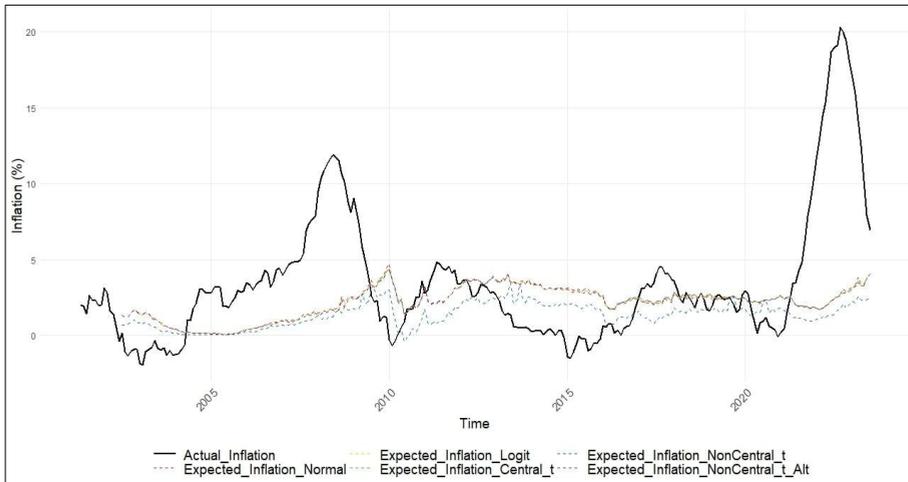


Figure 39. Latvian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.

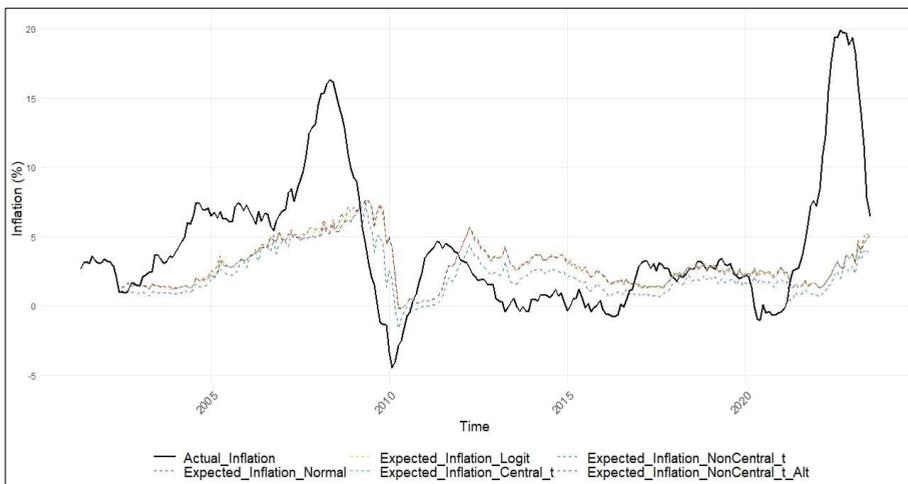


Figure 40. Estonian actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.

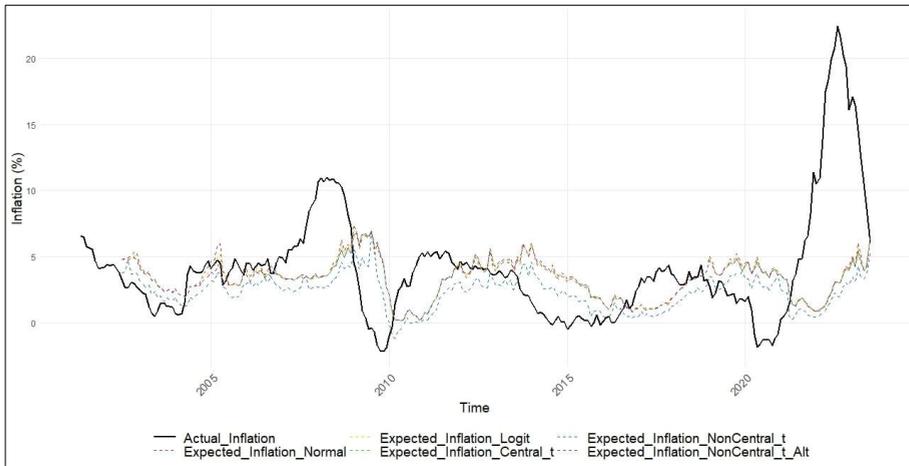


Figure 41. Polish actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter.

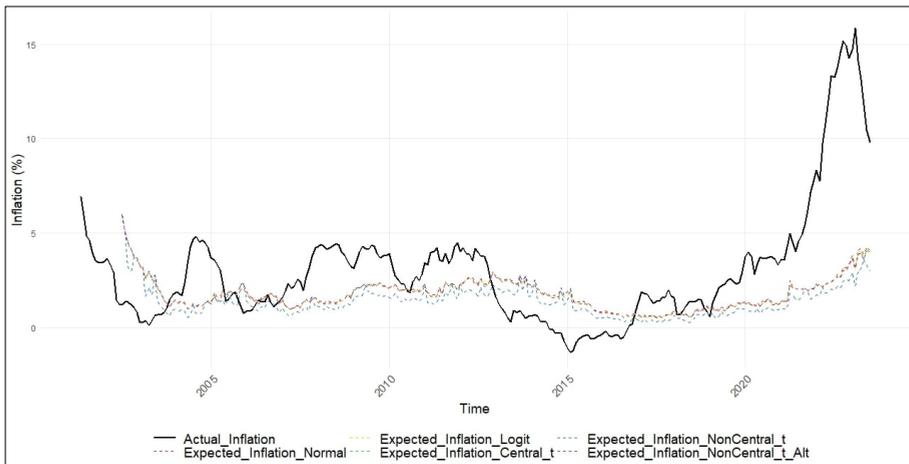
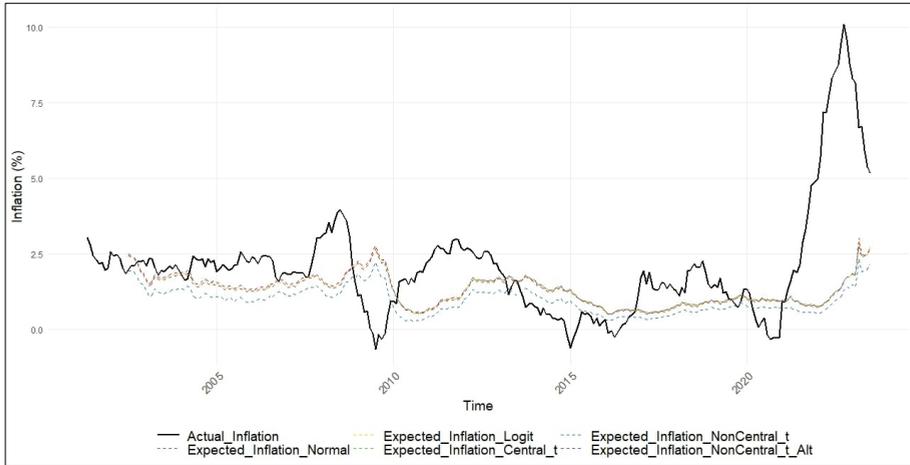


Figure 42. Euro area actual YoY inflation (π_{t+12}) and consumer quantified inflation expectations ($\pi_{e,t+12}$) using perceived YoY inflation (π_t^p) as a scaling parameter. When quantifying perceptions, running average is used as scaling parameter



ANNEX B

Table 27. Choi's modified P Unit-Root Test (specification with Individual Intercepts).

	<i>CONS_Y</i> <i>OY</i>	<i>RGDP_Y</i> <i>OY</i>	<i>GS_YOY</i>	<i>LOANS_</i> <i>YOY</i>	<i>PI_YOY</i>	<i>UN_YOY</i>	<i>i_YOY</i>	<i>DEPOSI</i> <i>TS YOY</i>	<i>WAGES_</i> <i>YOY</i>	<i>ENERG</i> <i>Y YOY</i>	<i>CCI_YO</i> <i>Y</i>	<i>BS_YOY</i>
<i>Statistic</i>	47.542	43.995	10.354	10.224	10.180	19.507	34.842	14.777	15.635	24.734	23.637	41.780
<i>p-value</i>	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

Table 28. PVAR FE OLS model results. Standard Errors in brackets. Significance *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

	CONS_YO Y	RGDP_YO Y	GS_YOY	LOANS_Y OY	PI_YOY	UN_YOY	BS_YOY	DEPOSITS _YOY	WAGES_Y OY	i_YOY	ENERGY_ YOY	CCI_YOY
lag1_CONS _YOY	0.4042 *** (0.0327)	-0.1643 *** (0.0250)	-0.0644 (0.0337)	-0.0510 (0.0261)	0.0500 *** (0.0099)	0.0132 * (0.0056)	0.0146 (0.1061)	-0.0112 (0.0410)	0.0541 * (0.0232)	-0.0191 ** (0.0064)	0.2246 ** (0.0868)	-0.2272 *** (0.0575)
lag1_RGDP _YOY	0.2036 *** (0.0431)	0.7104 *** (0.0330)	0.1383 ** (0.0444)	0.0779 * (0.0345)	0.0278 * (0.0131)	-0.0484 *** (0.0074)	0.5080 *** (0.1398)	-0.0079 (0.0540)	0.0296 (0.0306)	0.0551 *** (0.0084)	0.1712 (0.1144)	0.2887 *** (0.0758)
lag1_GS_Y OY	0.0519 * (0.0202)	0.0336 * (0.0155)	0.6117 *** (0.0208)	0.0293 (0.0162)	-0.0034 (0.0061)	-0.0052 (0.0035)	-0.0857 (0.0656)	-0.0541 * (0.0253)	0.0830 *** (0.0143)	-0.0108 ** (0.0039)	0.0467 (0.0537)	-0.0479 (0.0356)
lag1_LOA NS_YOY	-0.0136 (0.0111)	-0.0076 (0.0085)	0.0046 (0.0114)	0.9032 *** (0.0089)	-0.0003 (0.0034)	0.0080 *** (0.0019)	0.0243 (0.0360)	0.0477 *** (0.0139)	0.0092 (0.0079)	0.0024 (0.0022)	0.0236 (0.0295)	-0.0655 *** (0.0195)
lag1_PI_Y OY	-0.0784 (0.0515)	-0.0997 * (0.0394)	0.2250 *** (0.0531)	0.1330 ** (0.0412)	0.9122 *** (0.0156)	0.0216 * (0.0088)	-0.4764 ** (0.1670)	-0.2555 *** (0.0645)	0.1782 *** (0.0365)	0.0535 *** (0.0100)	0.6572 *** (0.1366)	0.1848 * (0.0905)
lag1_UN_Y OY	-0.1606 * (0.0759)	-0.1649 ** (0.0581)	-0.2189 ** (0.0783)	-0.0743 (0.0607)	0.0596 ** (0.0230)	0.7944 *** (0.0130)	1.0686 *** (0.2463)	-0.3632 *** (0.0951)	-0.1685 ** (0.0539)	0.0136 (0.0148)	0.4451 * (0.2015)	0.0539 (0.1335)
lag1_BS_Y OY	0.0161 ** (0.0059)	0.0257 *** (0.0045)	-0.0025 (0.0060)	0.0216 *** (0.0047)	0.0222 *** (0.0018)	-0.0047 *** (0.0010)	0.7199 *** (0.0190)	0.0032 (0.0073)	-0.0007 (0.0042)	0.0070 *** (0.0011)	0.1504 *** (0.0155)	-0.0997 *** (0.0103)
lag1_DEPO SITS_YOY	0.0192 * (0.0097)	0.0061 (0.0074)	0.0160 (0.0100)	0.0029 (0.0077)	0.0059 * (0.0029)	0.0035 * (0.0017)	-0.0137 (0.0314)	0.8168 *** (0.0121)	0.0065 (0.0069)	0.0008 (0.0019)	0.0354 (0.0257)	-0.0119 (0.0170)

lag1_WAG ES_YOY	0.0200 (0.0278)	0.0175 (0.0213)	0.0951 *** (0.0286)	0.0251 (0.0222)	-0.0035 (0.0084)	0.0134 ** (0.0048)	0.2379 ** (0.0901)	0.0539 (0.0348)	0.5976 *** (0.0197)	0.0035 (0.0054)	-0.1578 * (0.0737)	-0.0619 (0.0489)
lag1_i YO Y	-0.0942 (0.0724)	-0.0524 (0.0554)	-0.0000 (0.0746)	-0.2550 *** (0.0579)	-0.0583 ** (0.0219)	-0.0090 (0.0124)	-0.8294 *** (0.2347)	0.0922 (0.0907)	0.0983 (0.0513)	0.8109 *** (0.0141)	-0.7142 *** (0.1921)	-0.2189 (0.1273)
lag1_ENER GY_YOY	0.0270 ** (0.0089)	0.0179 ** (0.0068)	-0.0268 ** (0.0092)	-0.0200 ** (0.0071)	-0.0072 ** (0.0027)	-0.0023 (0.0015)	-0.0300 (0.0290)	0.0124 (0.0112)	-0.0203 ** (0.0063)	0.0010 (0.0017)	0.6241 *** (0.0237)	-0.0481 ** (0.0157)
lag1_CCI_ YOY	0.0727 *** (0.0119)	0.0676 *** (0.0091)	-0.0064 (0.0122)	0.0182 (0.0095)	-0.0134 *** (0.0036)	-0.0175 *** (0.0020)	0.3536 *** (0.0384)	-0.0184 (0.0148)	0.0044 (0.0084)	0.0029 (0.0023)	-0.0364 (0.0315)	0.6370 *** (0.0208)
Q1	-0.0350 (0.2525)	0.0968 (0.1932)	-0.1212 (0.2602)	0.1249 (0.2019)	0.0746 (0.0765)	0.0028 (0.0433)	-0.1550 (0.8189)	0.0930 (0.3164)	-0.0018 (0.1791)	0.0145 (0.0493)	0.3672 (0.6702)	0.1130 (0.4441)
Q2	-0.0347 (0.2497)	-0.0331 (0.1910)	0.0044 (0.2573)	0.0348 (0.1996)	0.0522 (0.0757)	0.0014 (0.0428)	-0.3725 (0.8097)	0.1507 (0.3128)	0.0488 (0.1771)	0.0050 (0.0487)	0.2660 (0.6626)	0.1494 (0.4390)
Q3	-0.0158 (0.2528)	0.0839 (0.1935)	-0.1288 (0.2606)	-0.0066 (0.2022)	0.0832 (0.0766)	0.0050 (0.0434)	-0.1232 (0.8200)	0.1192 (0.3168)	-0.2562 (0.1793)	0.0033 (0.0493)	0.9280 (0.6710)	-0.1837 (0.4446)

Table 29. PVAR GMM model results. Standard Errors in brackets. Significance *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S_YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
lag1_CO NS_YOY	0.0929 ** (0.0289)	0.0521 *** (0.0102)	-0.0236 (0.0171)	-0.0043 (0.0113)	0.0011 (0.0079)	-0.0119 (0.0070)	0.0683 *** (0.0170)	0.0950 *** (0.0128)	-0.0731 *** (0.0138)	0.0065 (0.0044)	0.0002 (0.0348)	0.1710 *** (0.0285)
lag1_RG DP_YOY	0.0778 ** (0.0238)	0.0381 *** (0.0071)	-0.0156 (0.0169)	0.0037 (0.0097)	-0.0048 (0.0076)	-0.0101 (0.0062)	0.0466 * (0.0188)	0.0809 *** (0.0111)	-0.0692 *** (0.0120)	0.0028 (0.0037)	-0.0050 (0.0338)	0.1512 *** (0.0246)
lag1_GS_ YOY	0.0194 ** (0.0059)	-0.0140 (0.0071)	0.0281 (0.0202)	0.0488 *** (0.0046)	-0.0027 (0.0046)	-0.0032 * (0.0014)	-0.1113 *** (0.0313)	0.0358 *** (0.0086)	-0.0587 *** (0.0075)	-0.0044 * (0.0020)	-0.0138 (0.0244)	0.0653 *** (0.0102)
lag1_LOA NS_YOY	0.0979 *** (0.0236)	0.0061 (0.0181)	0.0505 (0.0458)	0.1973 *** (0.0241)	0.0725 *** (0.0119)	-0.0163 * (0.0074)	-0.2786 *** (0.0822)	0.3534 *** (0.0309)	-0.1175 *** (0.0348)	0.0194 (0.0136)	0.1692 * (0.0683)	0.0986 ** (0.0313)
lag1_PI_ YOY	-0.0011 (0.0051)	0.0304 *** (0.0051)	0.0298 *** (0.0070)	0.0209 *** (0.0059)	0.0202 *** (0.0052)	-0.0036 (0.0022)	-0.0767 *** (0.0084)	-0.0122 * (0.0054)	0.0166 *** (0.0049)	0.0070 (0.0052)	0.0314 ** (0.0121)	-0.0208 *** (0.0041)
lag1_UN_ YOY	-0.0082 ** (0.0029)	-0.0049 *** (0.0013)	0.0046 (0.0049)	-0.0014 (0.0020)	0.0028 (0.0020)	0.0013 (0.0015)	0.0107 (0.0083)	-0.0171 *** (0.0027)	0.0175 *** (0.0028)	0.0003 (0.0009)	0.0036 (0.0173)	-0.0103 (0.0086)
lag1_BS_ YOY	0.0344 (0.0298)	-0.1120 *** (0.0245)	0.0540 * (0.0221)	0.0049 (0.0238)	-0.1213 * (0.0550)	0.0747 (0.0827)	0.8429 *** (0.0275)	0.0001 (0.0272)	-0.1175 *** (0.0248)	0.0328 (0.0518)	0.1964 *** (0.0334)	-0.0459 (0.0258)
lag1_DEP OSITS_Y	0.0315 (0.0371)	-0.0196 (0.0138)	-0.2330 *** (0.0400)	0.0546 * (0.0233)	0.0652 *** (0.0073)	-0.0143 * (0.0056)	0.0291 (0.0643)	0.3302 *** (0.0222)	-0.0761 * (0.0314)	0.0475 ** (0.0145)	0.2075 *** (0.0203)	0.0453 (0.0449)
lag1_WA GES_YO	-0.0055 (0.0079)	-0.0093 * (0.0044)	0.0140 * (0.0060)	0.0220 *** (0.0033)	-0.0032 ** (0.0010)	0.0037 * (0.0018)	-0.1060 *** (0.0203)	0.0112 ** (0.0042)	-0.0138 *** (0.0024)	-0.0020 (0.0012)	-0.0277 (0.0225)	-0.0303 *** (0.0089)
lag1_i_Y OY	-0.0004	0.0071 ***	0.0199 ***	0.0049 ***	-0.0034 ***	-0.0003	-0.0419 ***	-0.0112 ***	0.0037	-0.0035 ***	-0.0197	-0.0055

	(0.0020)	(0.0008)	(0.0030)	(0.0014)	(0.0009)	(0.0009)	(0.0071)	(0.0018)	(0.0019)	(0.0006)	(0.0147)	(0.0030)
lag1_ENE RGY YO	0.0512 (0.0301)	0.2474 *** (0.0470)	-0.0943 ** (0.0303)	0.1286 ** (0.0392)	0.2665 *** (0.0490)	-0.0499 (0.0319)	0.0154 (0.0630)	0.1886 *** (0.0427)	0.0100 (0.0283)	0.1299 * (0.0604)	0.7151 *** (0.0620)	-0.2656 *** (0.0284)
lag1_CCI YOY	0.0485 (0.0556)	-0.0518 *** (0.0132)	-0.0340 (0.0249)	-0.1134 *** (0.0332)	-0.0675 *** (0.0193)	-0.0217 (0.0158)	0.4723 *** (0.0623)	-0.0310 (0.0245)	-0.0515 *** (0.0152)	-0.0582 * (0.0260)	-0.1441 (0.1034)	0.5529 *** (0.0430)
Q1	-0.0003 *** (0.0001)	-0.0004 *** (0.0001)	-0.0001 (0.0002)	0.0001 *** (0.0000)	-0.0003 *** (0.0000)	0.0001 *** (0.0000)	-0.0026 *** (0.0006)	-0.0003 ** (0.0001)	-0.0003 *** (0.0000)	-0.0000 (0.0000)	-0.0012 *** (0.0003)	0.0010 *** (0.0002)
Q2	0.0001 ** (0.0001)	-0.0000 (0.0000)	0.0001 (0.0001)	0.0001 *** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0005 * (0.0002)	0.0003 *** (0.0000)	-0.0002 *** (0.0000)	-0.0000 *** (0.0000)	-0.0002 ** (0.0001)	0.0006 *** (0.0001)
Q3	0.0000 (0.0001)	0.0000 (0.0001)	0.0008 * (0.0003)	-0.0003 *** (0.0001)	-0.0004 *** (0.0001)	0.0001 ** (0.0000)	0.0013 ** (0.0005)	-0.0009 *** (0.0001)	0.0006 *** (0.0001)	-0.0002 ** (0.0001)	-0.0011 *** (0.0002)	0.0005 (0.0003)
const	-0.0003 ** (0.0001)	-0.0006 *** (0.0001)	-0.0004 * (0.0002)	0.0001 (0.0000)	-0.0002 *** (0.0000)	0.0001 *** (0.0000)	-0.0016 * (0.0007)	-0.0003 (0.0002)	-0.0004 *** (0.0001)	0.0000 (0.0000)	-0.0009 *** (0.0002)	0.0013 *** (0.0003)

Table 30. Forecast Error Variance Decomposition. Variable in consideration – CONS_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S_YOY	WAGES_ YOY	i_YOY	ENERGY _YOY	CCI_YO Y
t+1	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t+2	0.974	0.010	0.004	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.001	0.009
t+3	0.938	0.025	0.008	0.000	0.000	0.002	0.000	0.002	0.000	0.001	0.002	0.021
t+4	0.908	0.038	0.011	0.000	0.001	0.003	0.000	0.002	0.000	0.002	0.002	0.033
t+5	0.885	0.046	0.012	0.001	0.002	0.004	0.001	0.003	0.000	0.003	0.002	0.041
t+6	0.869	0.051	0.013	0.001	0.003	0.005	0.002	0.003	0.000	0.003	0.002	0.047
t+7	0.859	0.053	0.013	0.002	0.005	0.006	0.003	0.003	0.000	0.004	0.002	0.050
t+8	0.852	0.054	0.013	0.002	0.007	0.006	0.005	0.003	0.000	0.004	0.002	0.051

Table 31. Forecast Error Variance Decomposition. Variable in consideration – RGDP_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S_YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.611	0.389	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t+2	0.547	0.432	0.003	0.000	0.000	0.002	0.002	0.000	0.000	0.000	0.001	0.012
t+3	0.502	0.452	0.006	0.000	0.001	0.003	0.004	0.000	0.000	0.001	0.001	0.030
t+4	0.473	0.459	0.008	0.000	0.003	0.005	0.003	0.000	0.000	0.001	0.001	0.046
t+5	0.454	0.460	0.009	0.000	0.007	0.006	0.003	0.000	0.000	0.002	0.001	0.058
t+6	0.442	0.457	0.009	0.000	0.012	0.007	0.005	0.000	0.000	0.002	0.001	0.065
t+7	0.435	0.453	0.009	0.001	0.016	0.007	0.007	0.000	0.000	0.002	0.001	0.068
t+8	0.430	0.448	0.009	0.001	0.020	0.008	0.010	0.001	0.000	0.002	0.001	0.069

Table 32. Forecast Error Variance Decomposition. Variable in consideration – GS_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.010	0.007	0.983	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t+2	0.013	0.016	0.965	0.000	0.000	0.001	0.000	0.000	0.003	0.000	0.002	0.000
t+3	0.017	0.024	0.943	0.000	0.001	0.002	0.000	0.001	0.007	0.000	0.004	0.000
t+4	0.021	0.032	0.921	0.000	0.002	0.005	0.000	0.001	0.010	0.000	0.007	0.000
t+5	0.026	0.038	0.901	0.000	0.004	0.007	0.001	0.002	0.012	0.000	0.009	0.000
t+6	0.031	0.044	0.882	0.000	0.005	0.009	0.001	0.002	0.013	0.000	0.010	0.001
t+7	0.035	0.049	0.867	0.000	0.007	0.011	0.002	0.003	0.014	0.000	0.011	0.002
t+8	0.038	0.053	0.854	0.000	0.007	0.012	0.002	0.003	0.014	0.000	0.012	0.004

Table 33. Forecast Error Variance Decomposition. Variable in consideration – LOANS_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.009	0.007	0.036	0.949	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t+2	0.011	0.012	0.044	0.925	0.000	0.000	0.003	0.000	0.000	0.002	0.002	0.001
t+3	0.014	0.018	0.052	0.898	0.000	0.001	0.006	0.000	0.001	0.005	0.004	0.002
t+4	0.016	0.023	0.057	0.871	0.000	0.001	0.008	0.000	0.001	0.009	0.008	0.005
t+5	0.018	0.028	0.062	0.847	0.000	0.001	0.010	0.000	0.002	0.013	0.012	0.007
t+6	0.019	0.031	0.066	0.826	0.000	0.002	0.010	0.000	0.002	0.017	0.016	0.010
t+7	0.020	0.033	0.069	0.809	0.001	0.002	0.009	0.000	0.003	0.021	0.019	0.013
t+8	0.020	0.035	0.072	0.795	0.001	0.003	0.009	0.000	0.003	0.025	0.022	0.015

Table 34. Forecast Error Variance Decomposition. Variable in consideration – PI_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.034	0.001	0.000	0.000	0.965	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t+2	0.084	0.002	0.001	0.000	0.879	0.000	0.030	0.000	0.000	0.001	0.001	0.002
t+3	0.124	0.004	0.001	0.000	0.794	0.001	0.069	0.001	0.000	0.002	0.001	0.002
t+4	0.154	0.006	0.001	0.000	0.725	0.002	0.102	0.002	0.000	0.004	0.002	0.002
t+5	0.174	0.010	0.001	0.000	0.672	0.002	0.125	0.003	0.001	0.006	0.003	0.002
t+6	0.188	0.013	0.001	0.000	0.632	0.003	0.140	0.004	0.001	0.010	0.004	0.005
t+7	0.197	0.016	0.001	0.000	0.602	0.004	0.148	0.005	0.002	0.013	0.005	0.008
t+8	0.202	0.018	0.001	0.000	0.581	0.004	0.152	0.006	0.002	0.017	0.006	0.012

Table 35. Forecast Error Variance Decomposition. Variable in consideration – UN_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.121	0.038	0.003	0.002	0.000	0.837	0.000	0.000	0.000	0.000	0.000	0.000
t+2	0.159	0.075	0.005	0.001	0.000	0.744	0.000	0.000	0.002	0.000	0.000	0.013
t+3	0.174	0.110	0.006	0.001	0.002	0.669	0.000	0.001	0.004	0.000	0.000	0.034
t+4	0.175	0.137	0.006	0.002	0.004	0.613	0.000	0.001	0.005	0.000	0.000	0.056
t+5	0.168	0.156	0.006	0.003	0.009	0.573	0.001	0.002	0.007	0.000	0.000	0.075
t+6	0.159	0.168	0.006	0.005	0.015	0.544	0.004	0.003	0.008	0.000	0.000	0.090
t+7	0.150	0.173	0.005	0.008	0.020	0.523	0.007	0.004	0.009	0.000	0.000	0.099
t+8	0.144	0.175	0.005	0.011	0.026	0.508	0.012	0.005	0.010	0.000	0.000	0.104

Table 36. Forecast Error Variance Decomposition. Variable in consideration – BS_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S_YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.013	0.001	0.001	0.001	0.072	0.001	0.911	0.000	0.000	0.000	0.000	0.000
t+2	0.035	0.008	0.001	0.001	0.053	0.001	0.879	0.000	0.001	0.001	0.001	0.018
t+3	0.045	0.017	0.001	0.001	0.047	0.002	0.831	0.000	0.003	0.004	0.003	0.047
t+4	0.047	0.023	0.001	0.001	0.051	0.003	0.785	0.000	0.004	0.007	0.005	0.073
t+5	0.045	0.026	0.001	0.001	0.062	0.004	0.749	0.000	0.005	0.010	0.007	0.090
t+6	0.044	0.026	0.001	0.001	0.074	0.004	0.726	0.000	0.005	0.012	0.009	0.098
t+7	0.046	0.025	0.002	0.001	0.084	0.004	0.711	0.000	0.005	0.013	0.009	0.099
t+8	0.050	0.025	0.001	0.001	0.091	0.005	0.701	0.000	0.005	0.013	0.010	0.097

Table 37. Forecast Error Variance Decomposition. Variable in consideration – DEPOSITS_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S_YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.000	0.000	0.000	0.006	0.001	0.000	0.000	0.991	0.000	0.000	0.000	0.000
t+2	0.000	0.000	0.002	0.004	0.002	0.002	0.001	0.987	0.001	0.000	0.000	0.000
t+3	0.000	0.000	0.002	0.003	0.005	0.005	0.001	0.981	0.001	0.000	0.001	0.000
t+4	0.000	0.000	0.003	0.003	0.009	0.008	0.001	0.972	0.001	0.000	0.001	0.000
t+5	0.000	0.001	0.003	0.004	0.013	0.011	0.001	0.962	0.002	0.001	0.002	0.000
t+6	0.000	0.001	0.003	0.005	0.019	0.015	0.001	0.951	0.002	0.001	0.002	0.001
t+7	0.000	0.002	0.003	0.006	0.025	0.018	0.001	0.939	0.002	0.001	0.002	0.001
t+8	0.000	0.003	0.003	0.007	0.031	0.021	0.001	0.926	0.002	0.001	0.003	0.002

Table 38. Forecast Error Variance Decomposition. Variable in consideration – WAGES_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.001	0.003	0.052	0.000	0.000	0.001	0.000	0.004	0.940	0.000	0.000	0.000
t+2	0.011	0.002	0.084	0.000	0.000	0.001	0.000	0.004	0.894	0.001	0.002	0.000
t+3	0.028	0.005	0.106	0.000	0.002	0.003	0.000	0.004	0.844	0.002	0.006	0.000
t+4	0.044	0.012	0.118	0.001	0.004	0.006	0.000	0.005	0.798	0.003	0.008	0.001
t+5	0.059	0.020	0.124	0.001	0.006	0.008	0.001	0.005	0.759	0.003	0.011	0.003
t+6	0.070	0.029	0.125	0.001	0.009	0.011	0.001	0.005	0.727	0.004	0.012	0.005
t+7	0.078	0.038	0.124	0.001	0.011	0.013	0.002	0.005	0.702	0.004	0.013	0.008
t+8	0.084	0.045	0.123	0.001	0.012	0.014	0.003	0.006	0.683	0.004	0.014	0.011

Table 39. Forecast Error Variance Decomposition. Variable in consideration – i_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.000	0.016	0.000	0.005	0.011	0.004	0.002	0.003	0.003	0.957	0.000	0.000
t+2	0.007	0.042	0.001	0.005	0.028	0.003	0.004	0.002	0.003	0.903	0.000	0.000
t+3	0.017	0.068	0.003	0.006	0.047	0.003	0.013	0.002	0.004	0.836	0.000	0.002
t+4	0.029	0.091	0.004	0.006	0.061	0.002	0.025	0.002	0.004	0.769	0.000	0.005
t+5	0.040	0.110	0.005	0.006	0.071	0.002	0.037	0.001	0.004	0.712	0.000	0.011
t+6	0.049	0.125	0.005	0.006	0.077	0.002	0.047	0.001	0.005	0.666	0.000	0.017
t+7	0.056	0.136	0.005	0.006	0.081	0.002	0.054	0.001	0.005	0.631	0.001	0.024
t+8	0.060	0.144	0.005	0.006	0.082	0.002	0.058	0.001	0.005	0.605	0.001	0.030

Table 40. Forecast Error Variance Decomposition. Variable in consideration – ENERGY_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YO Y	LOANS_Y OY	PI_YOY	UN_YO Y	BS_YO Y	DEPOSITS_Y OY	WAGES_Y OY	i_YOY	ENERGY_ YOY	CCI_YO Y
t+1	0.011	0.001	0.000	0.001	0.407	0.002	0.000	0.001	0.002	0.006	0.570	0.000
t+2	0.035	0.001	0.000	0.001	0.424	0.002	0.025	0.001	0.005	0.010	0.496	0.000
t+3	0.058	0.001	0.000	0.001	0.420	0.004	0.056	0.002	0.006	0.015	0.439	0.000
t+4	0.074	0.003	0.000	0.001	0.408	0.005	0.081	0.002	0.006	0.021	0.400	0.001
t+5	0.085	0.004	0.000	0.001	0.394	0.006	0.097	0.003	0.005	0.027	0.375	0.003
t+6	0.091	0.005	0.000	0.001	0.383	0.007	0.105	0.004	0.005	0.033	0.360	0.006
t+7	0.093	0.006	0.001	0.001	0.376	0.007	0.108	0.005	0.005	0.039	0.352	0.009
t+8	0.094	0.006	0.001	0.001	0.371	0.008	0.108	0.005	0.005	0.043	0.347	0.012

Table 41. Forecast Error Variance Decomposition. Variable in consideration – CCI_YOY.

	CONS_Y OY	RGDP_Y OY	GS_YOY	LOANS_ YOY	PI_YOY	UN_YOY	BS_YOY	DEPOSIT S YOY	WAGES_ YOY	i_YOY	ENERGY YOY	CCI_YO Y
t+1	0.064	0.020	0.021	0.002	0.050	0.007	0.098	0.001	0.000	0.000	0.010	0.727
t+2	0.048	0.029	0.016	0.001	0.061	0.006	0.155	0.001	0.001	0.000	0.016	0.666
t+3	0.041	0.031	0.014	0.002	0.066	0.006	0.202	0.001	0.002	0.000	0.019	0.617
t+4	0.041	0.030	0.013	0.003	0.067	0.005	0.234	0.001	0.003	0.000	0.020	0.583
t+5	0.044	0.029	0.013	0.005	0.066	0.005	0.252	0.001	0.004	0.000	0.020	0.561
t+6	0.046	0.029	0.014	0.006	0.065	0.005	0.259	0.001	0.005	0.000	0.020	0.549
t+7	0.048	0.029	0.015	0.007	0.064	0.005	0.261	0.001	0.005	0.001	0.020	0.543
t+8	0.048	0.030	0.015	0.009	0.064	0.005	0.260	0.002	0.006	0.001	0.020	0.540

Figure 43. PVAR FE OLS model impulse response functions when impulse is CONS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

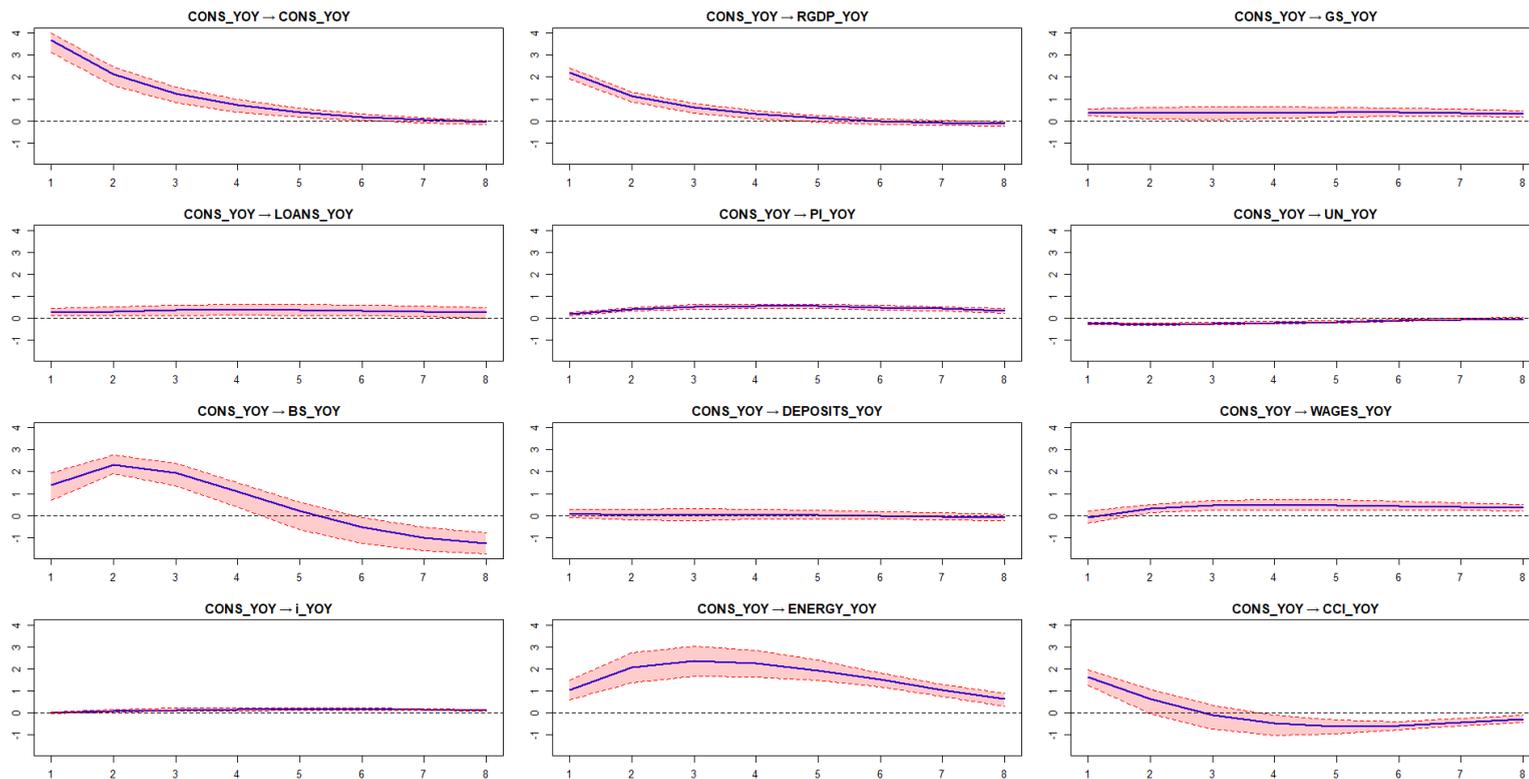


Figure 44. PVAR FE OLS model impulse response functions when impulse is RGDP_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

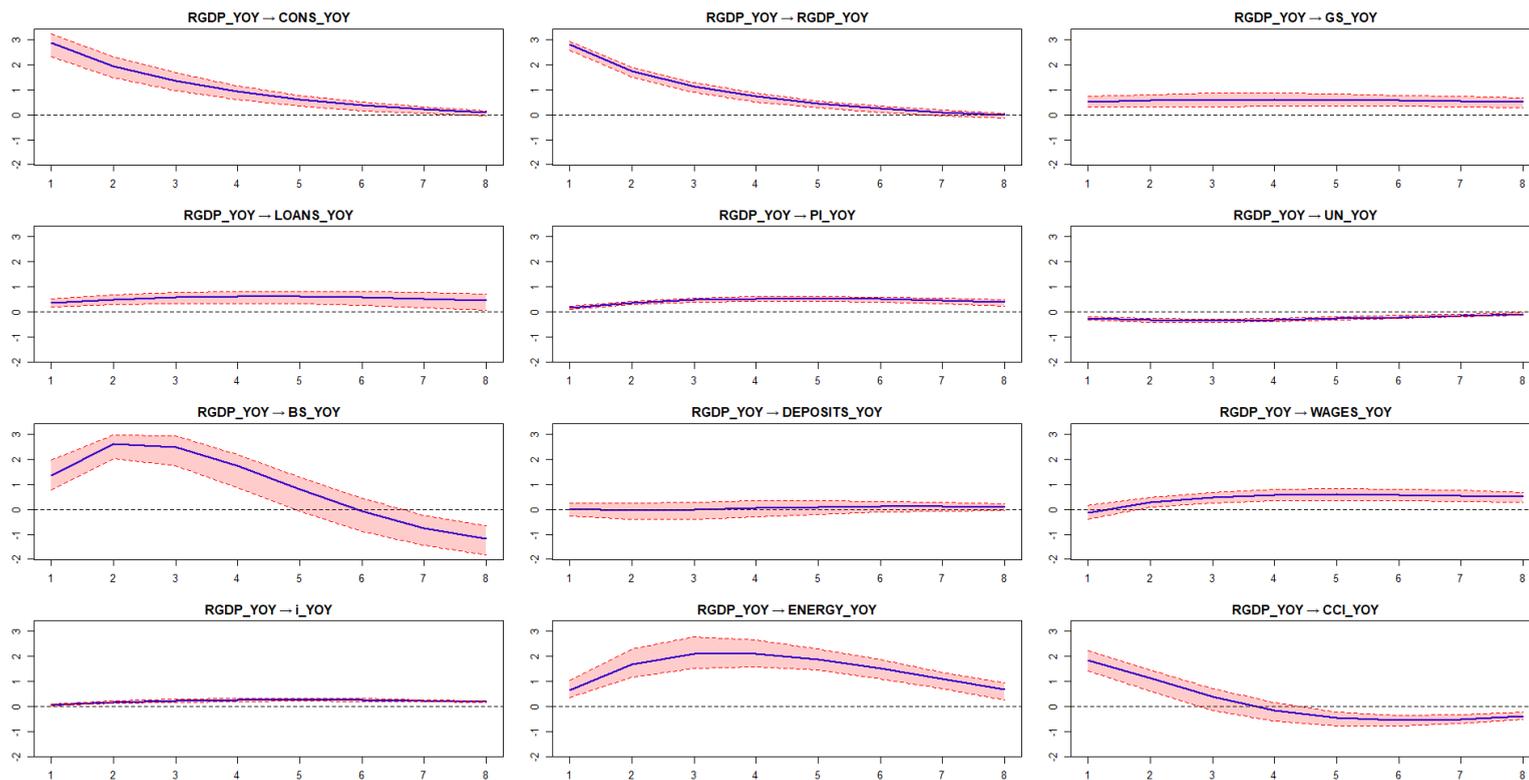


Figure 45. PVAR FE OLS model impulse response functions when impulse is GS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

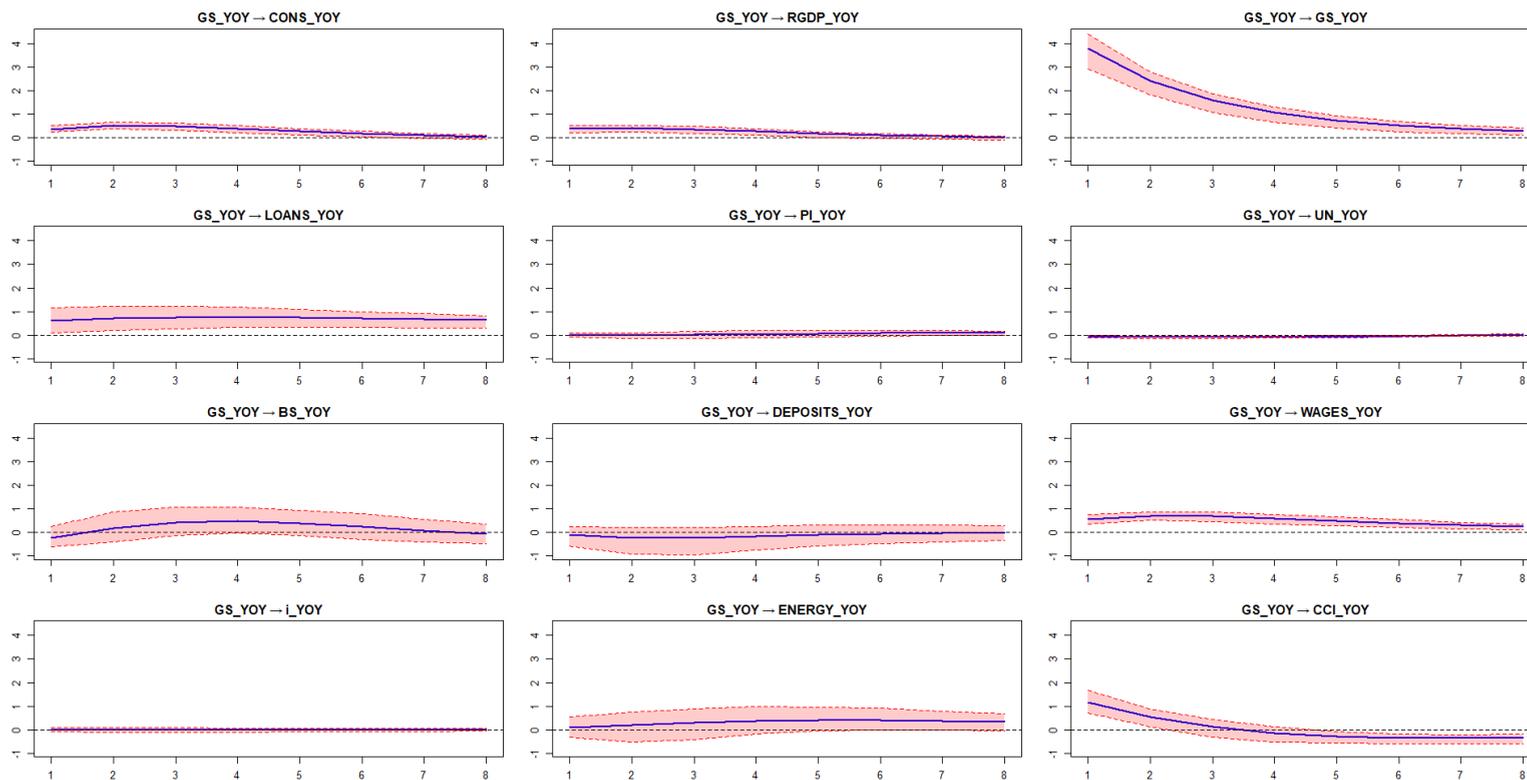


Figure 46. PVAR FE OLS model impulse response functions when impulse is LOANS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

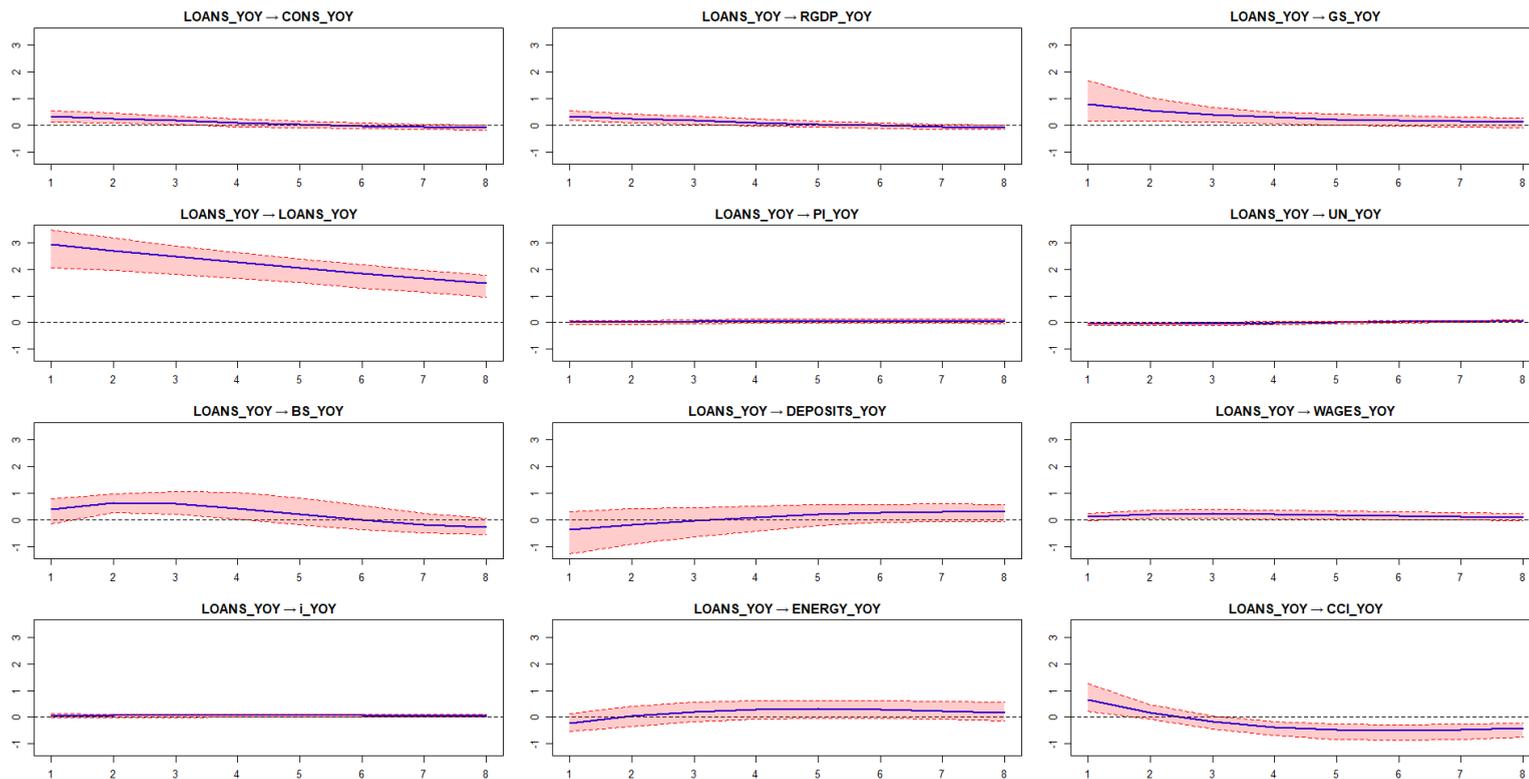


Figure 47. PVAR FE OLS model impulse response functions when impulse is PI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

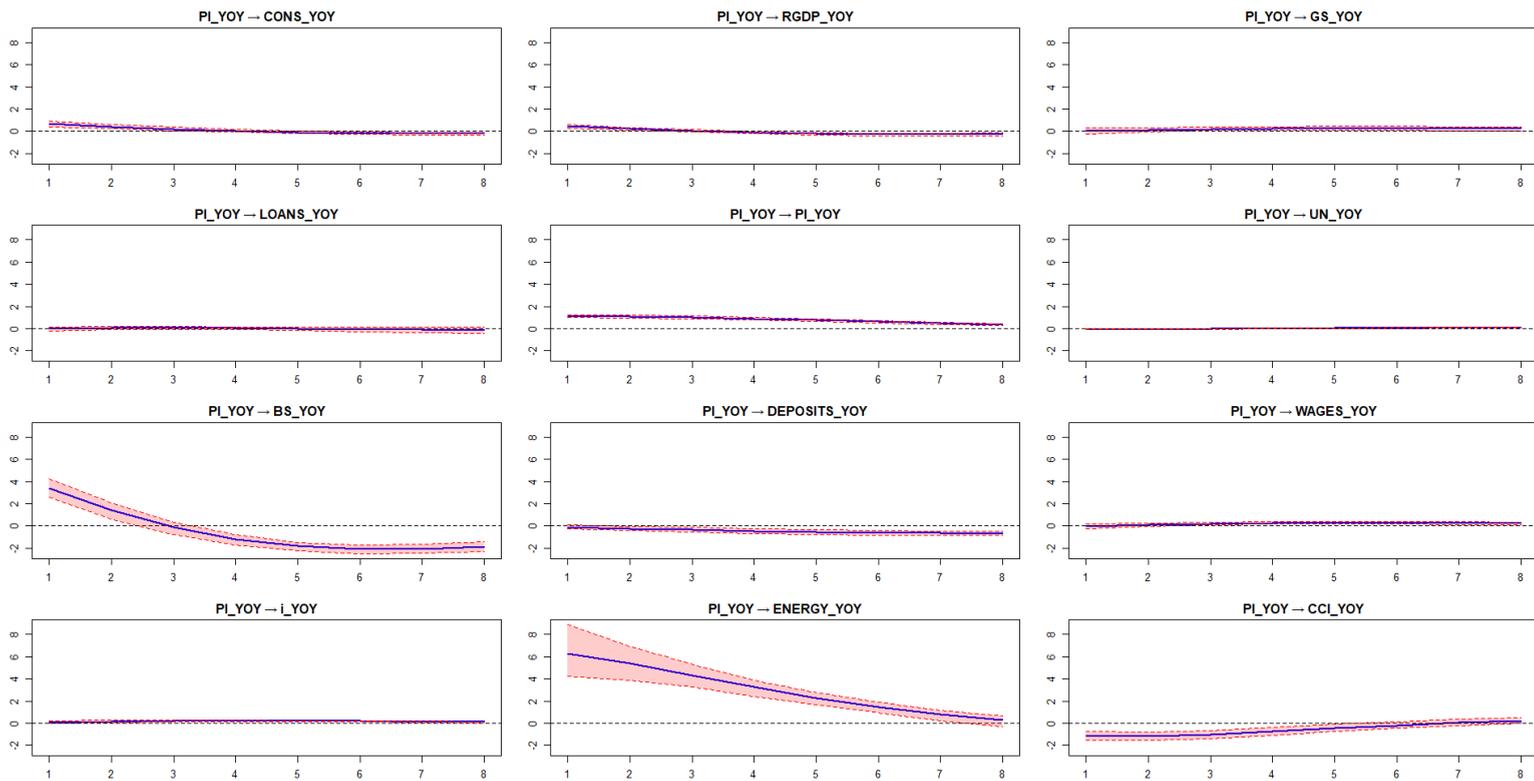


Figure 48. PVAR FE OLS model impulse response functions when impulse is UN_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

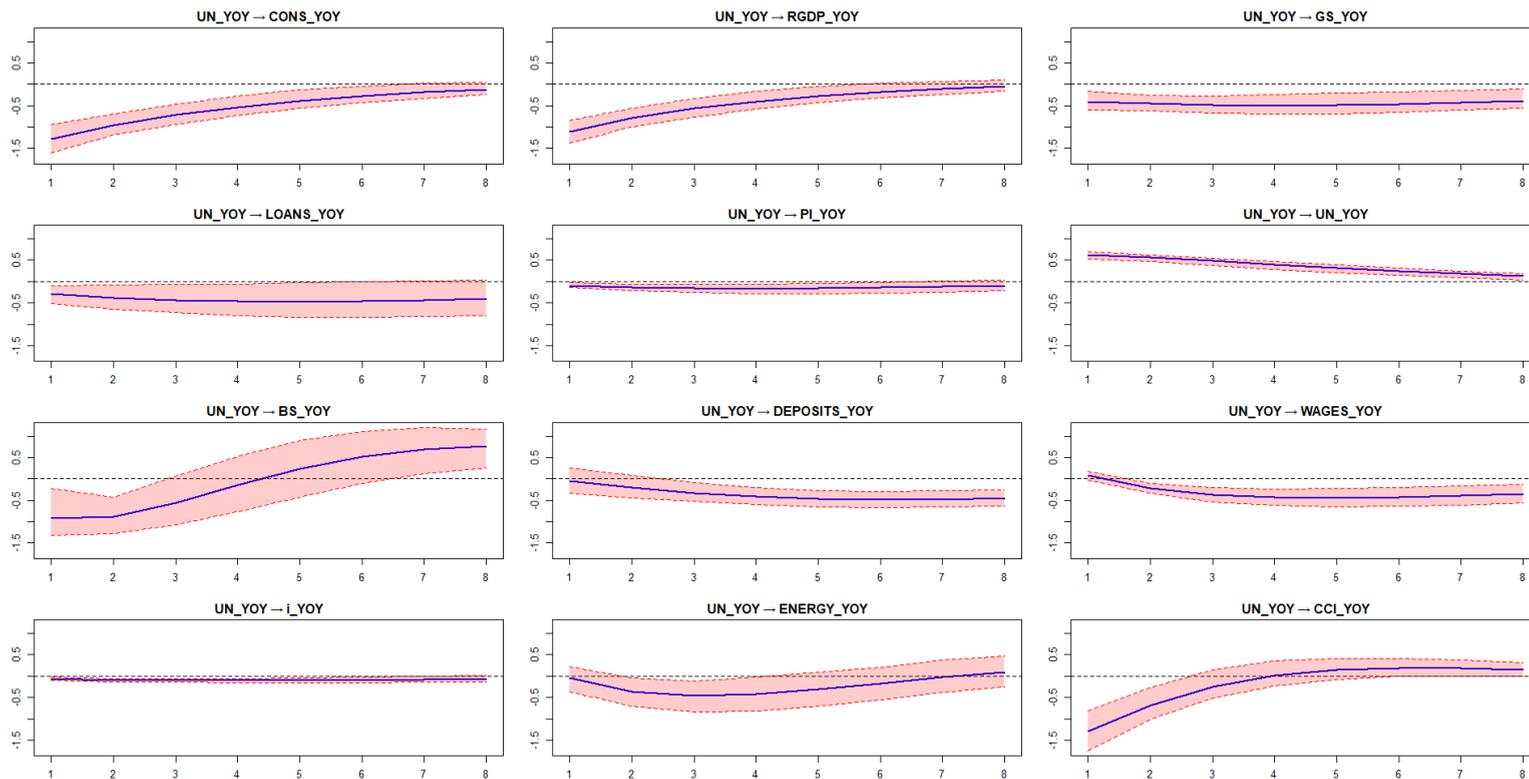


Figure 49. PVAR FE OLS model impulse response functions when impulse is BS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

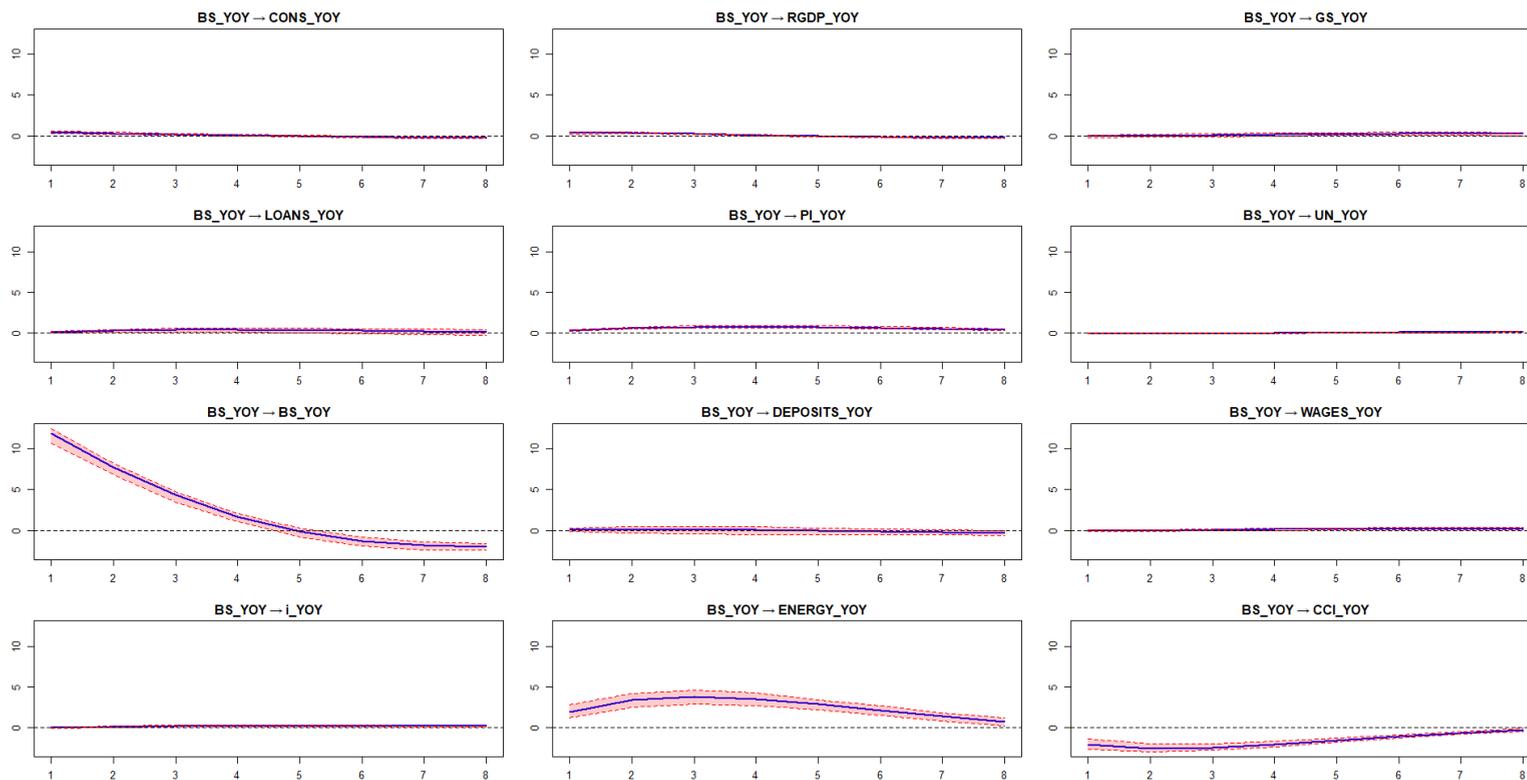


Figure 50. PVAR FE OLS model impulse response functions when impulse is DEPOSITS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

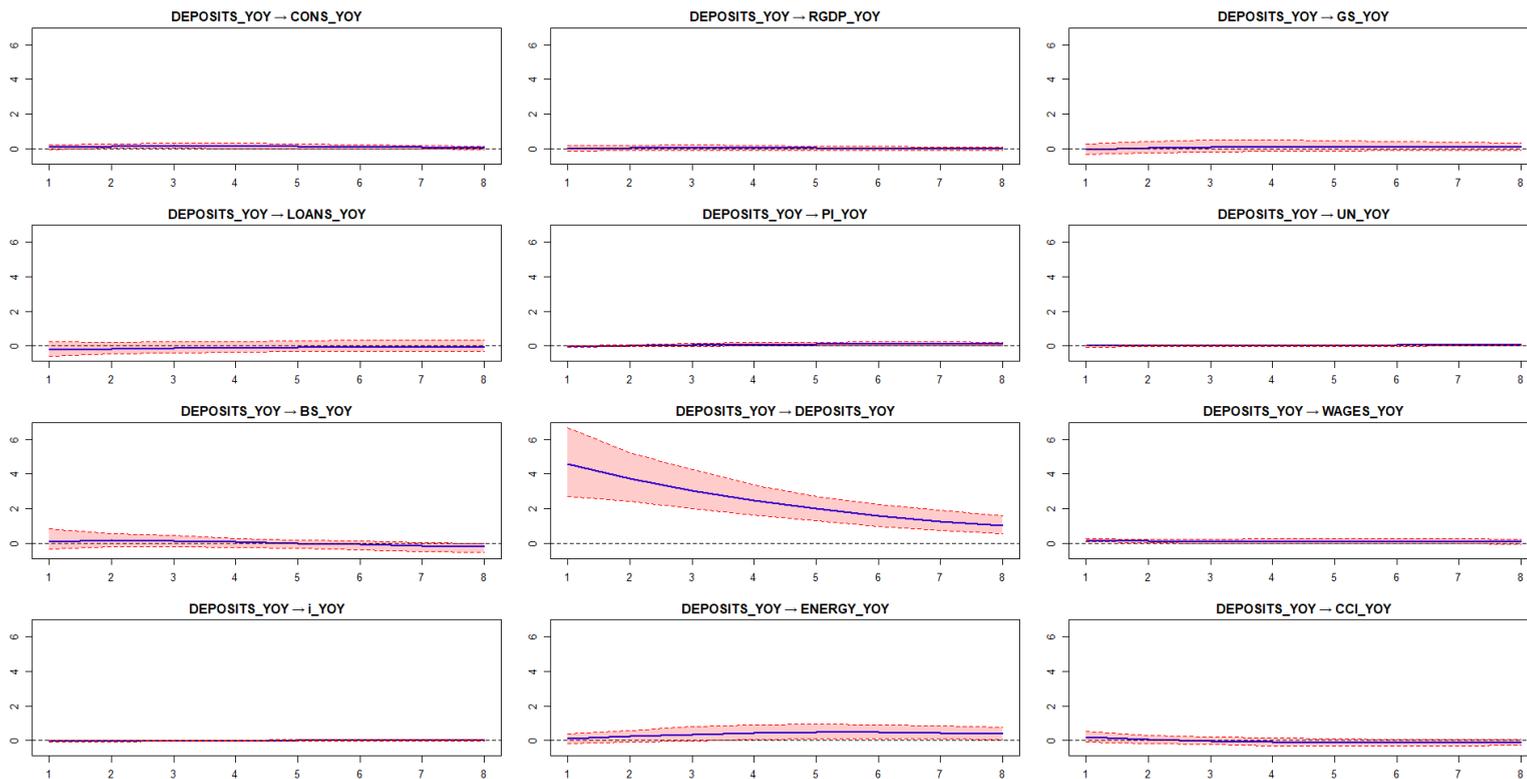


Figure 51. PVAR FE OLS model impulse response functions when impulse is WAGES_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

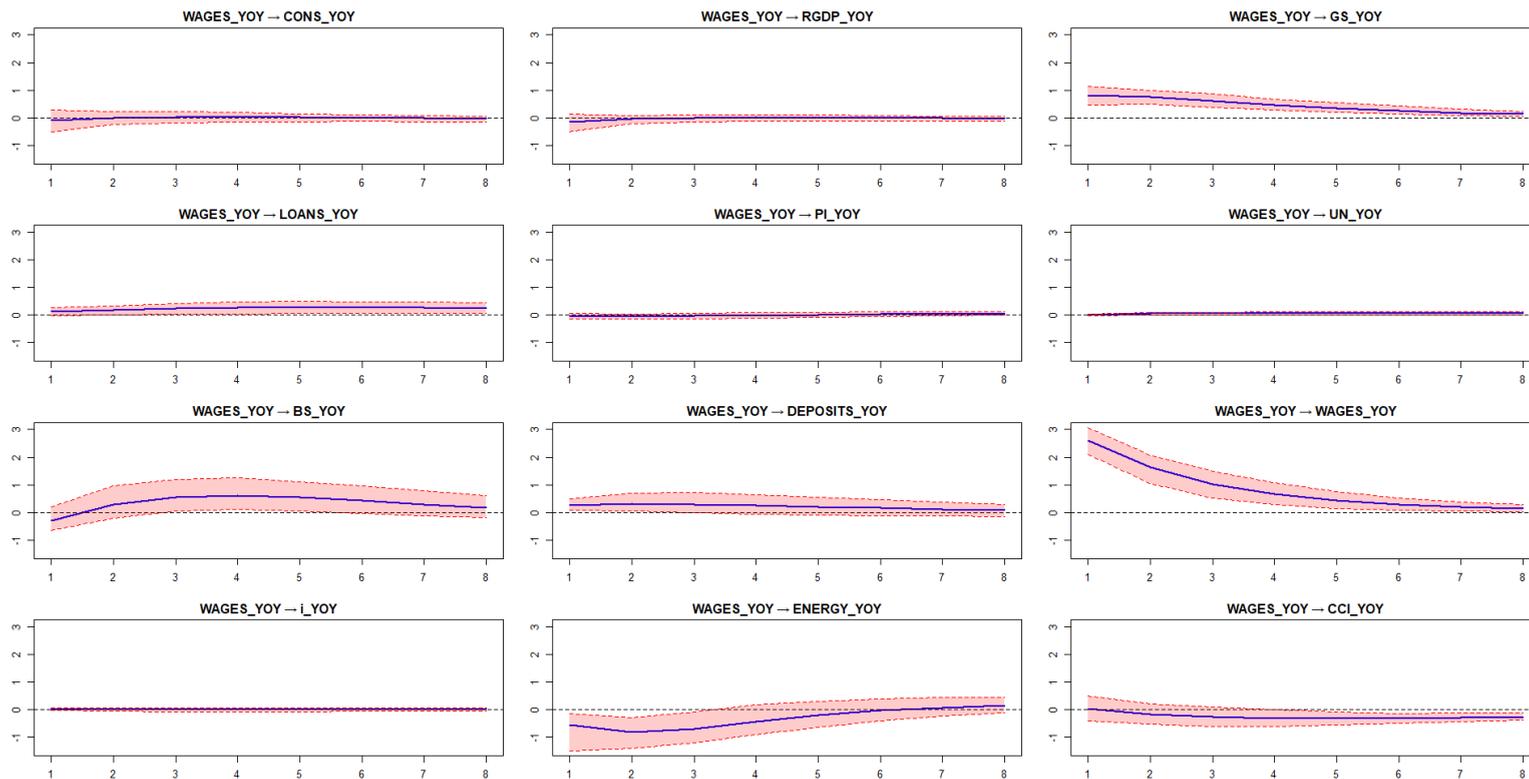


Figure 52. PVAR FE OLS model impulse response functions when impulse is i_YOY . Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

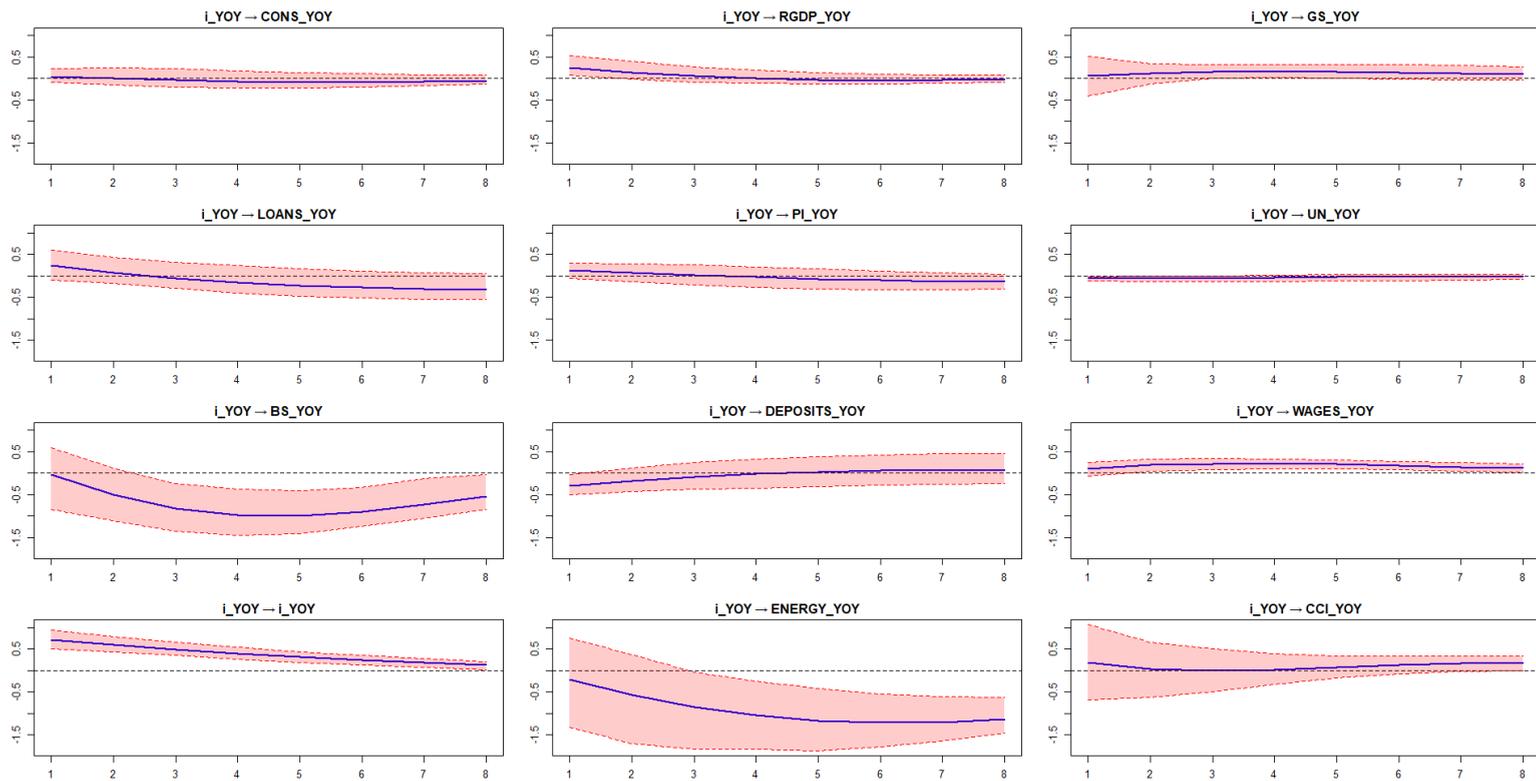


Figure 53. PVAR FE OLS model impulse response functions when impulse is ENERGY_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

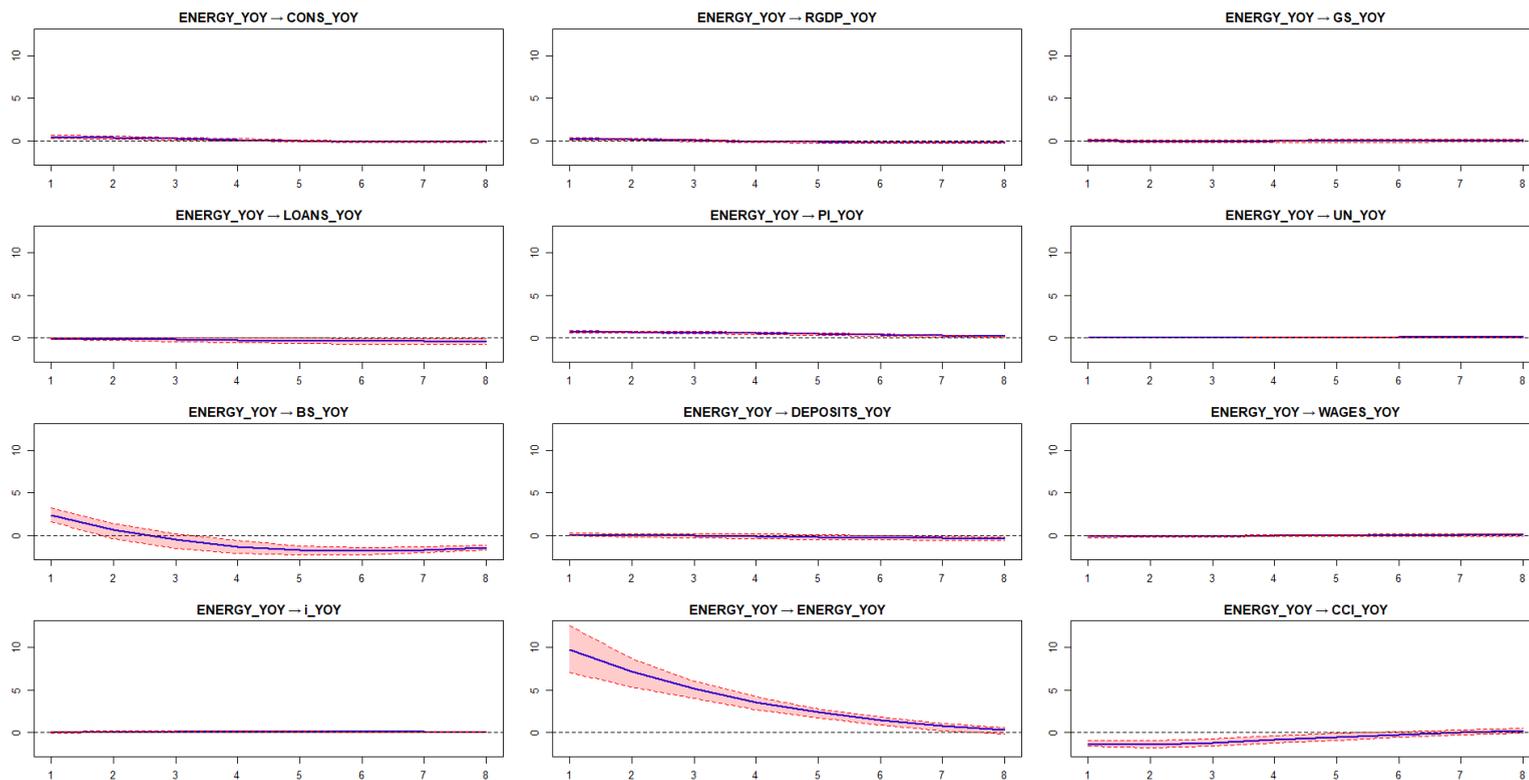


Figure 54. PVAR FE OLS model impulse response functions when impulse is CCI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

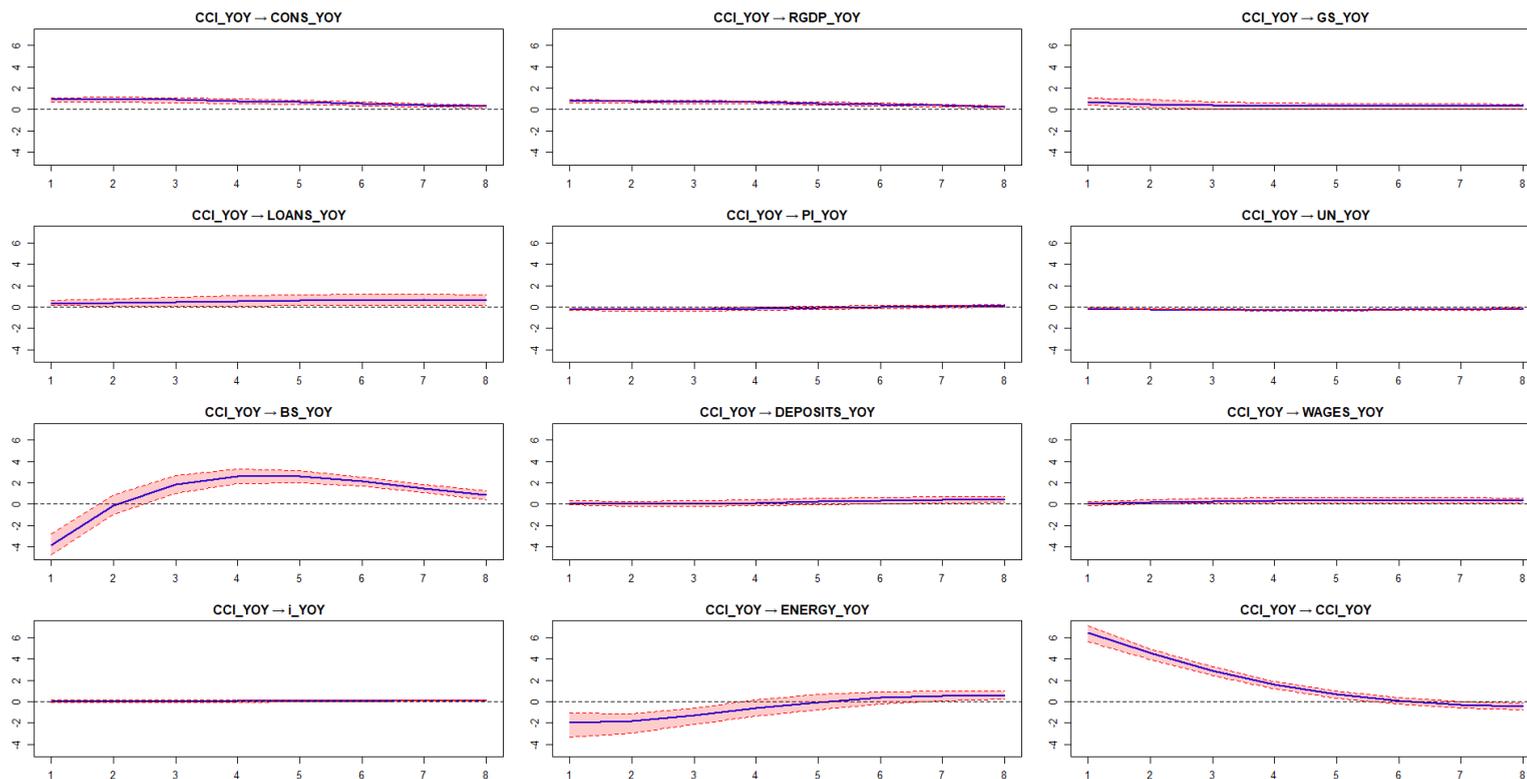


Figure 55. PVAR GMM system model impulse response functions when impulse is CONS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

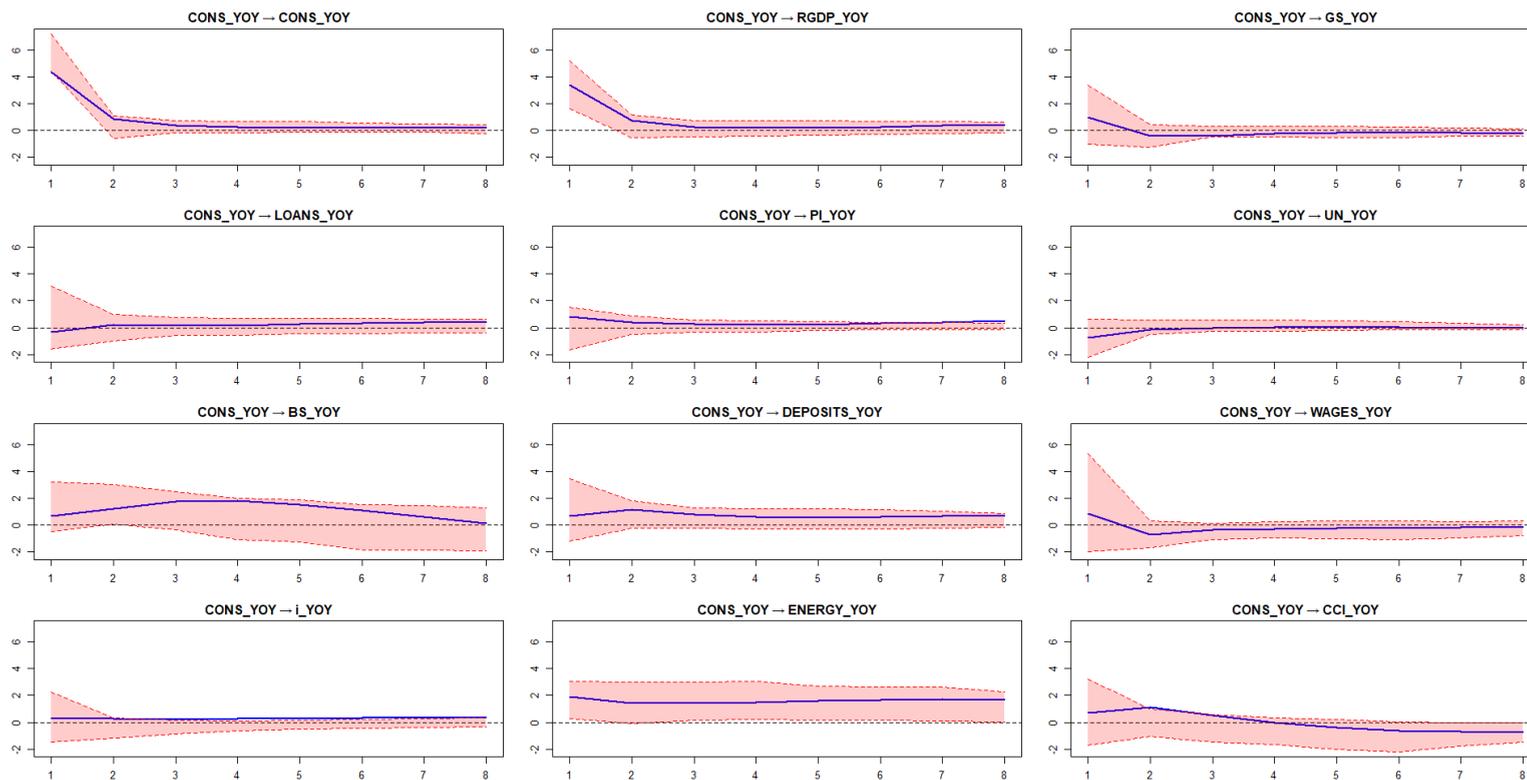


Figure 56. PVAR GMM system model impulse response functions when impulse is RGDP_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

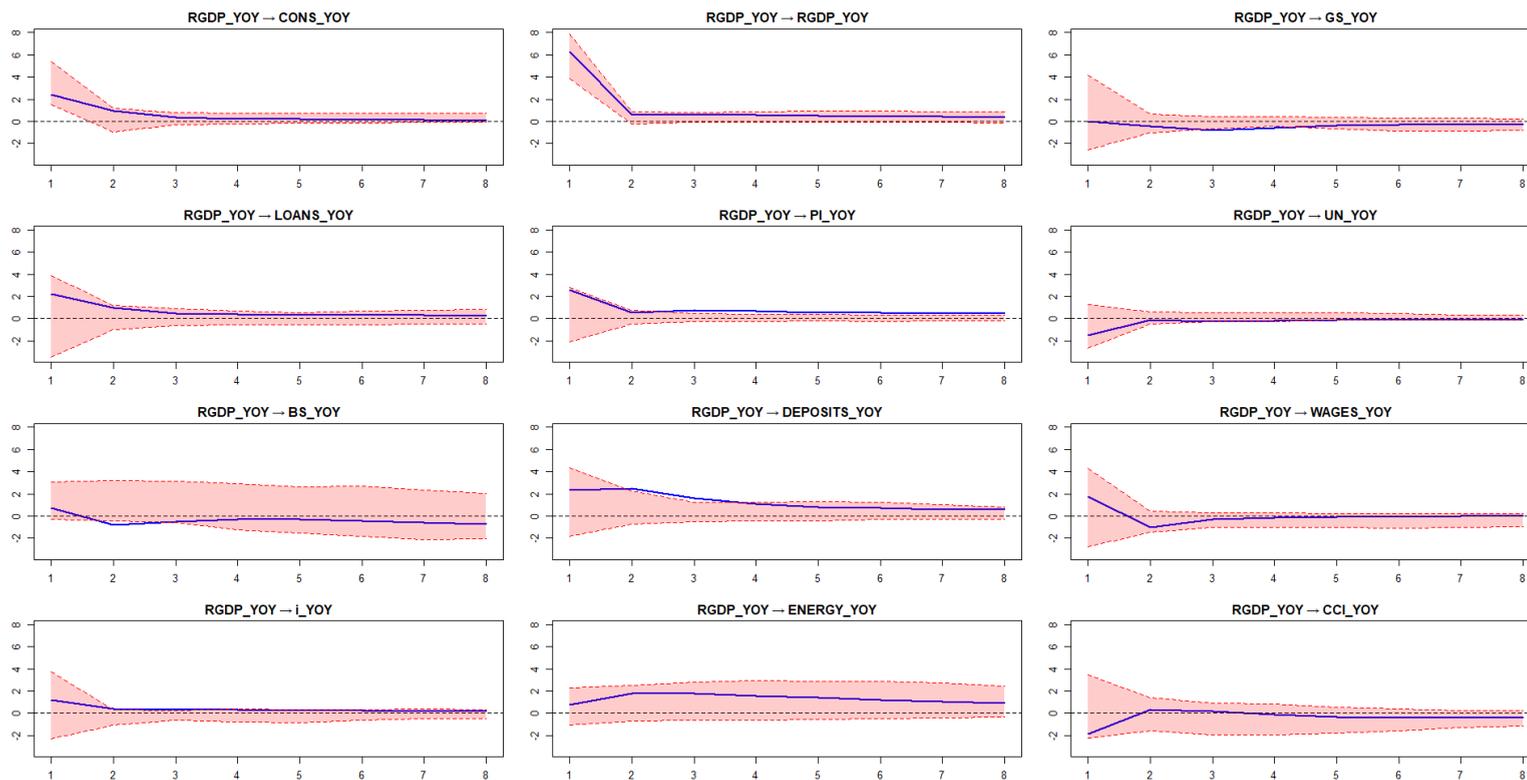


Figure 57. PVAR GMM system model impulse response functions when impulse is GS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

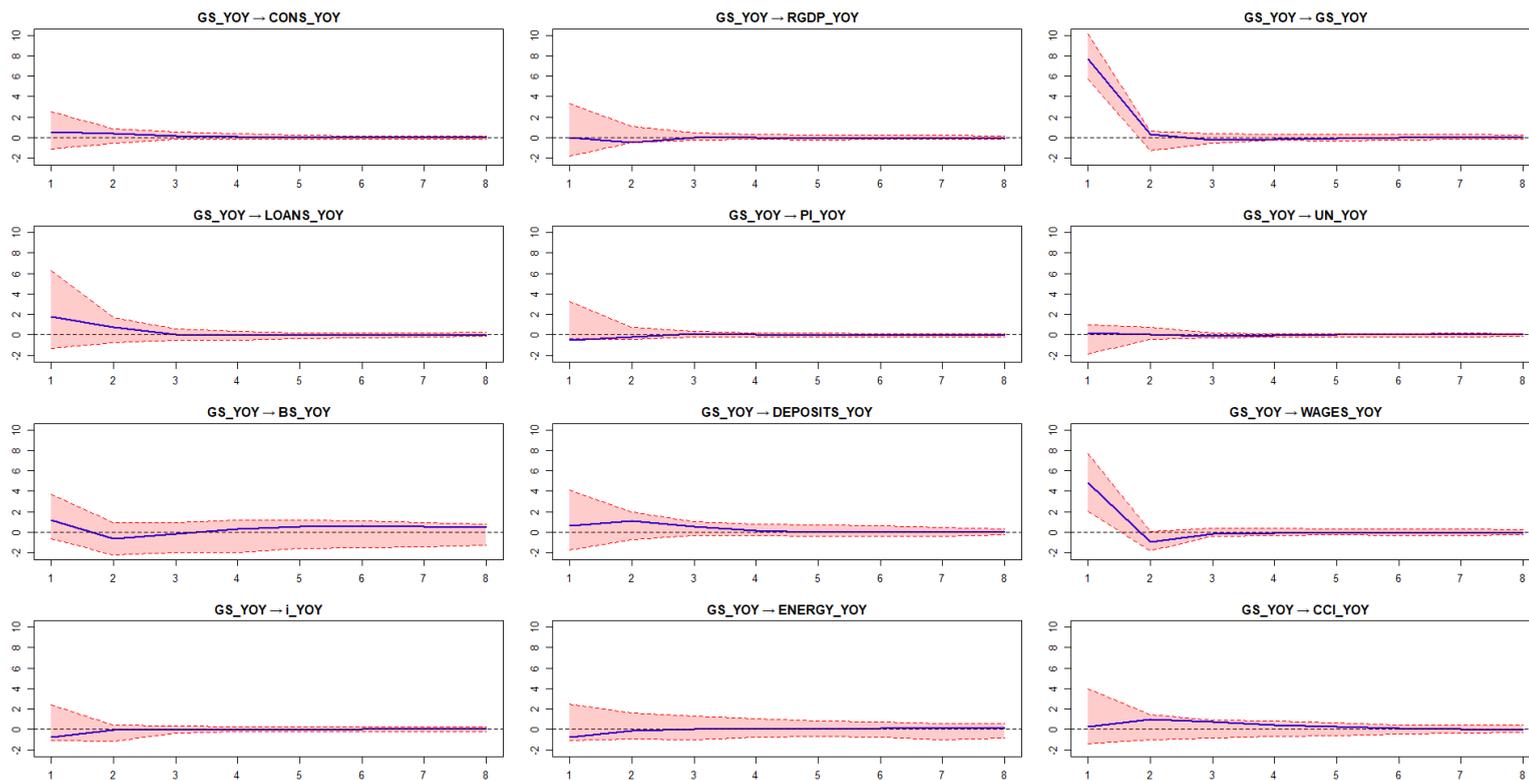


Figure 58. PVAR GMM system model impulse response functions when impulse is LOANS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

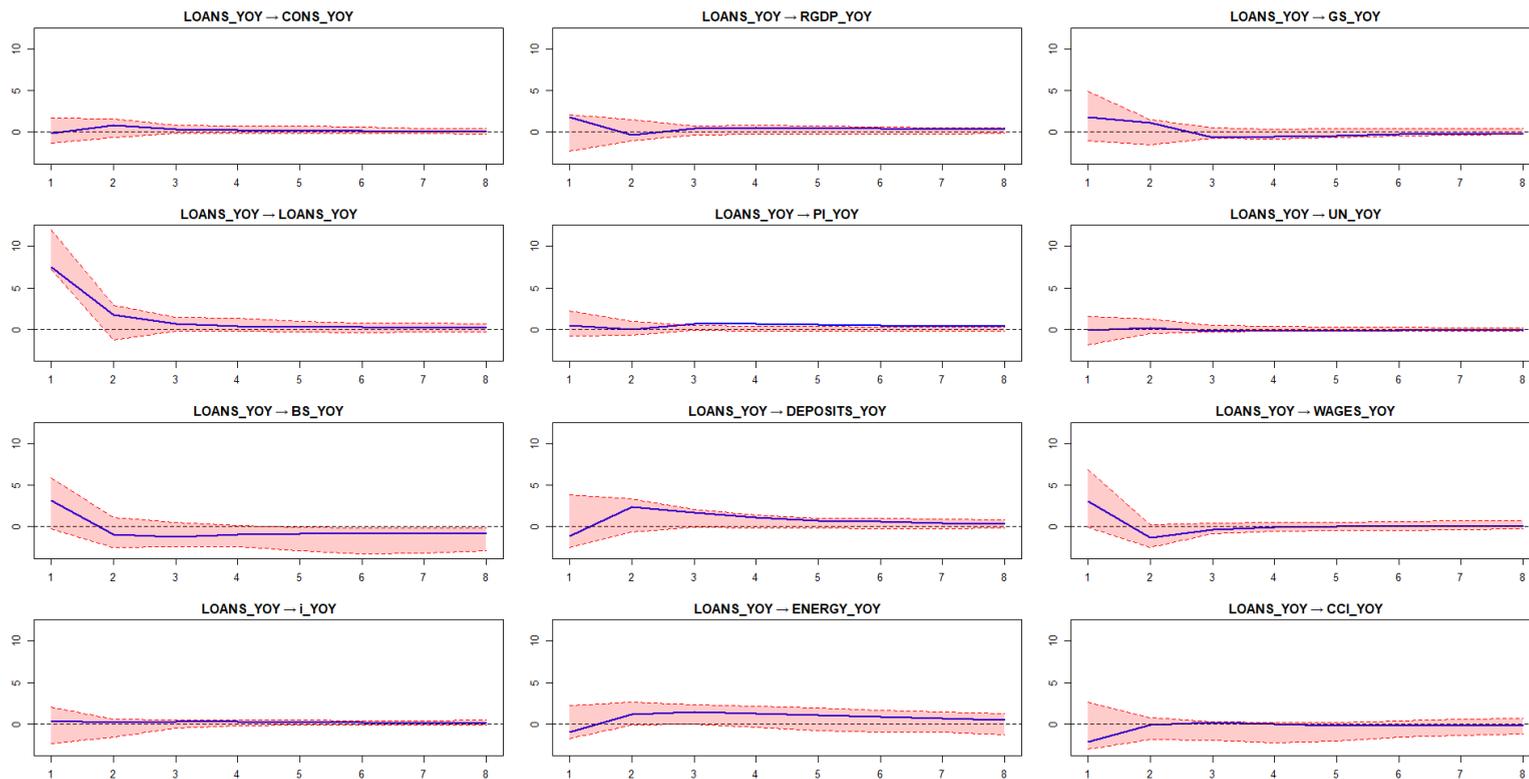


Figure 59. PVAR GMM system model impulse response functions when impulse is PI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

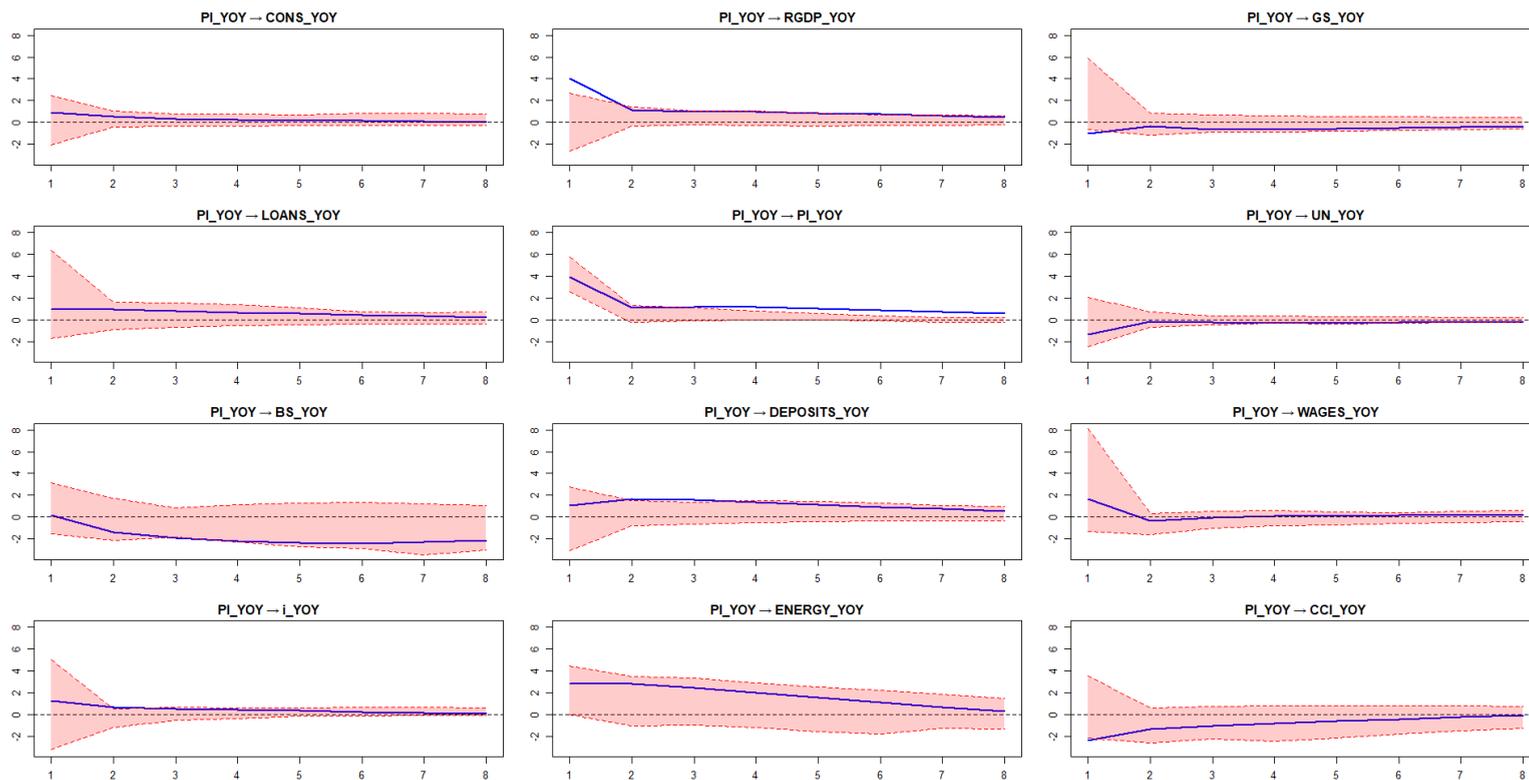


Figure 60. PVAR GMM system model impulse response functions when impulse is UN_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

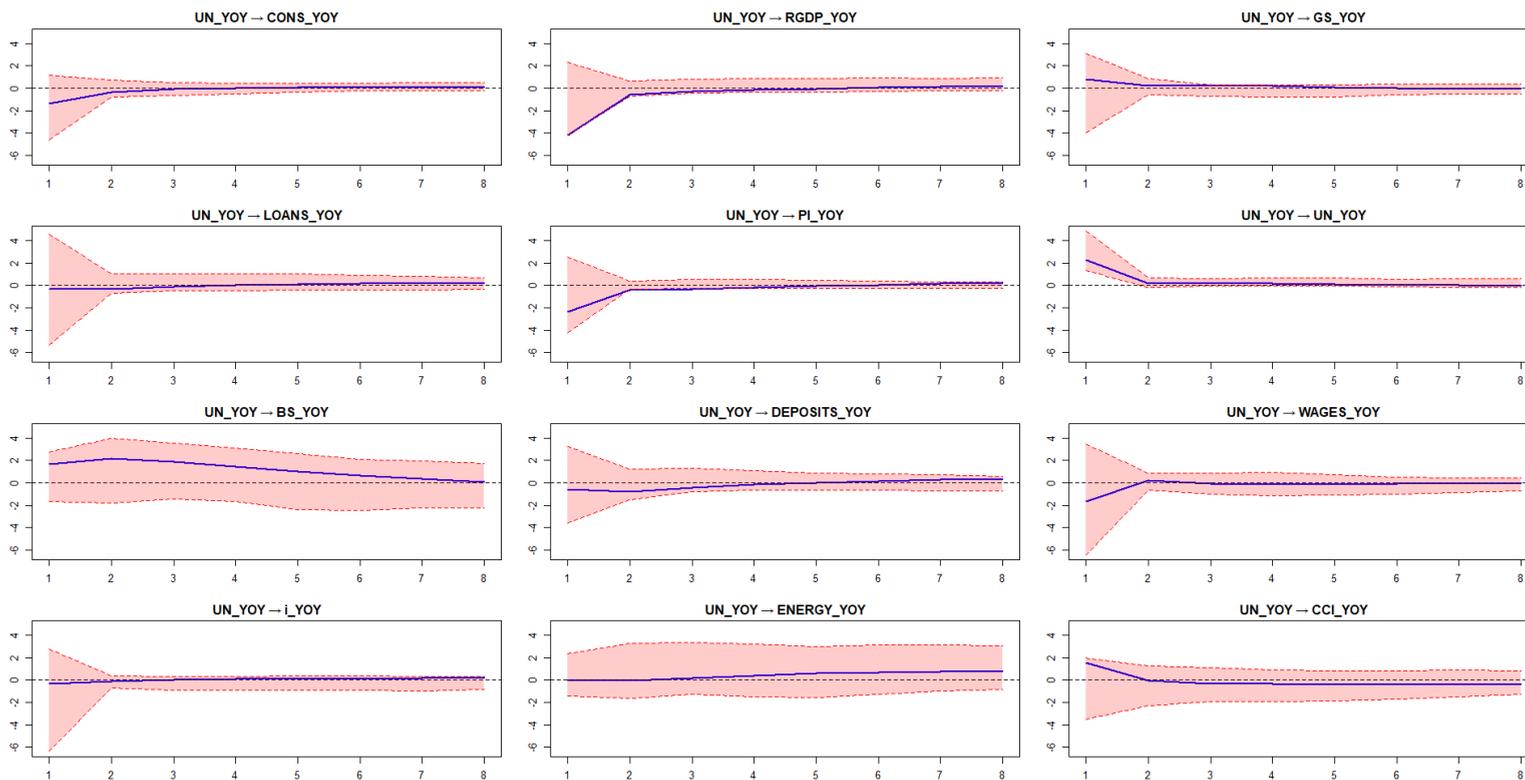


Figure 61. PVAR GMM system model impulse response functions when impulse is BS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

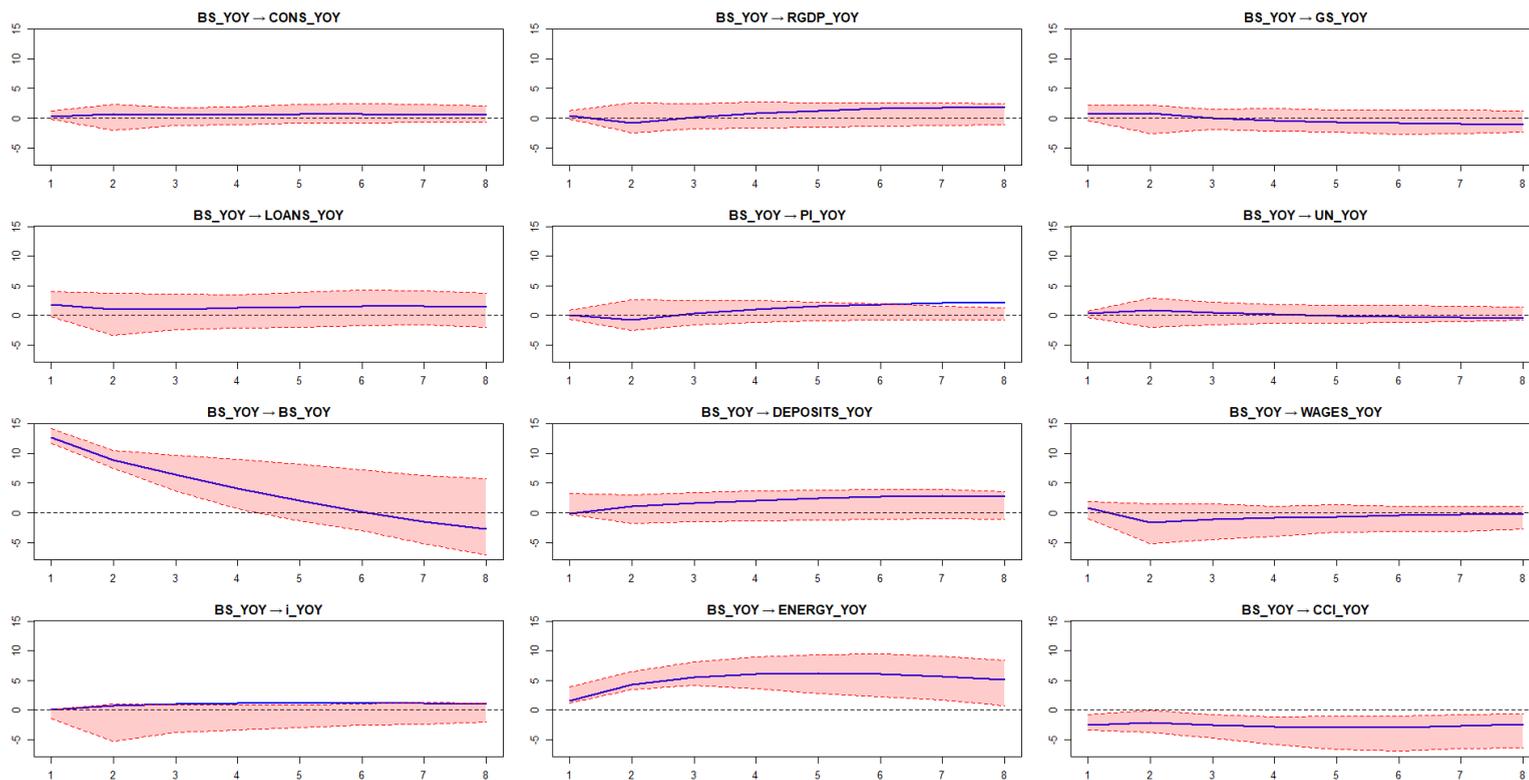


Figure 62. PVAR GMM system model impulse response functions when impulse is DEPOSITS_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

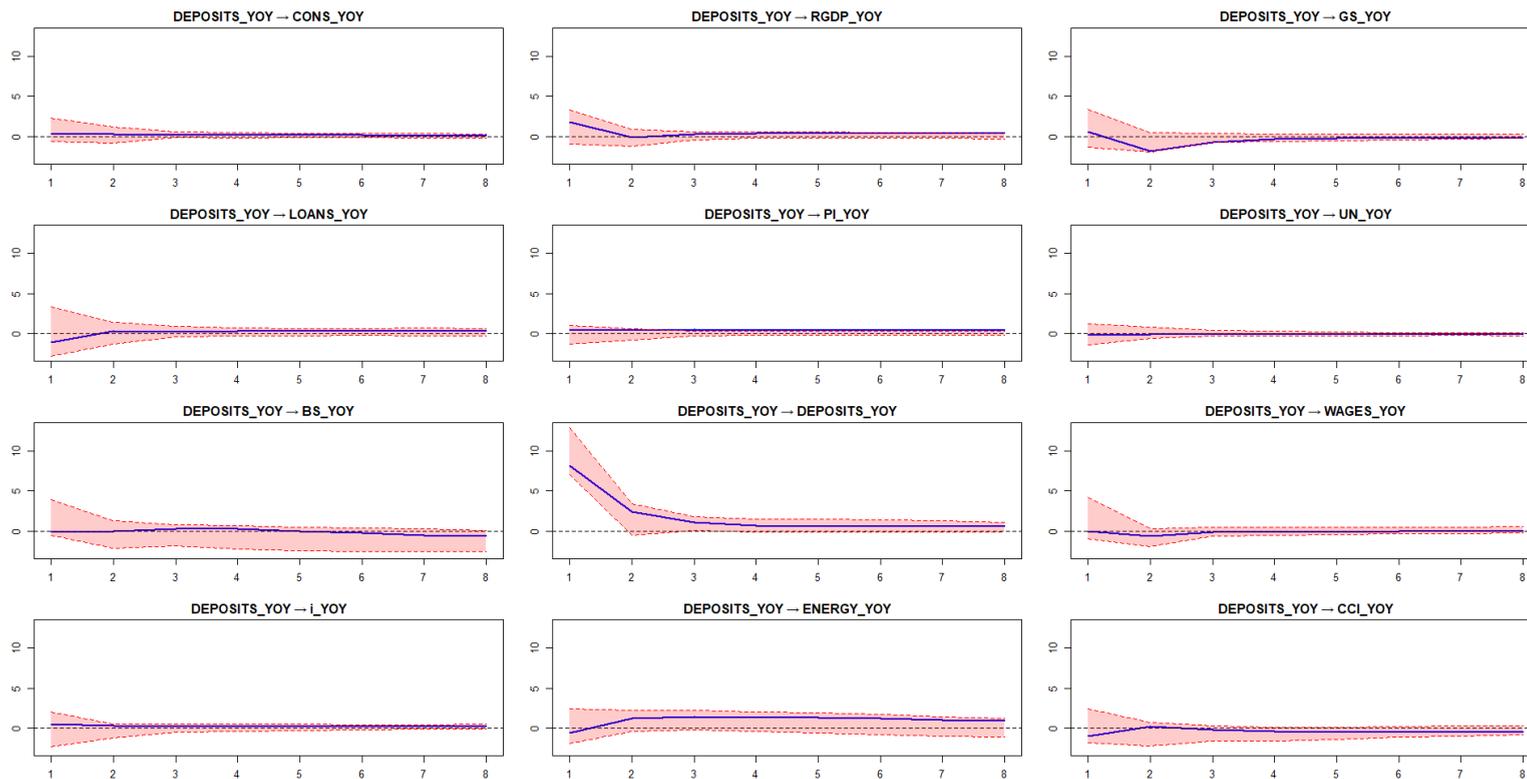


Figure 63. PVAR GMM system model impulse response functions when impulse is WAGES_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

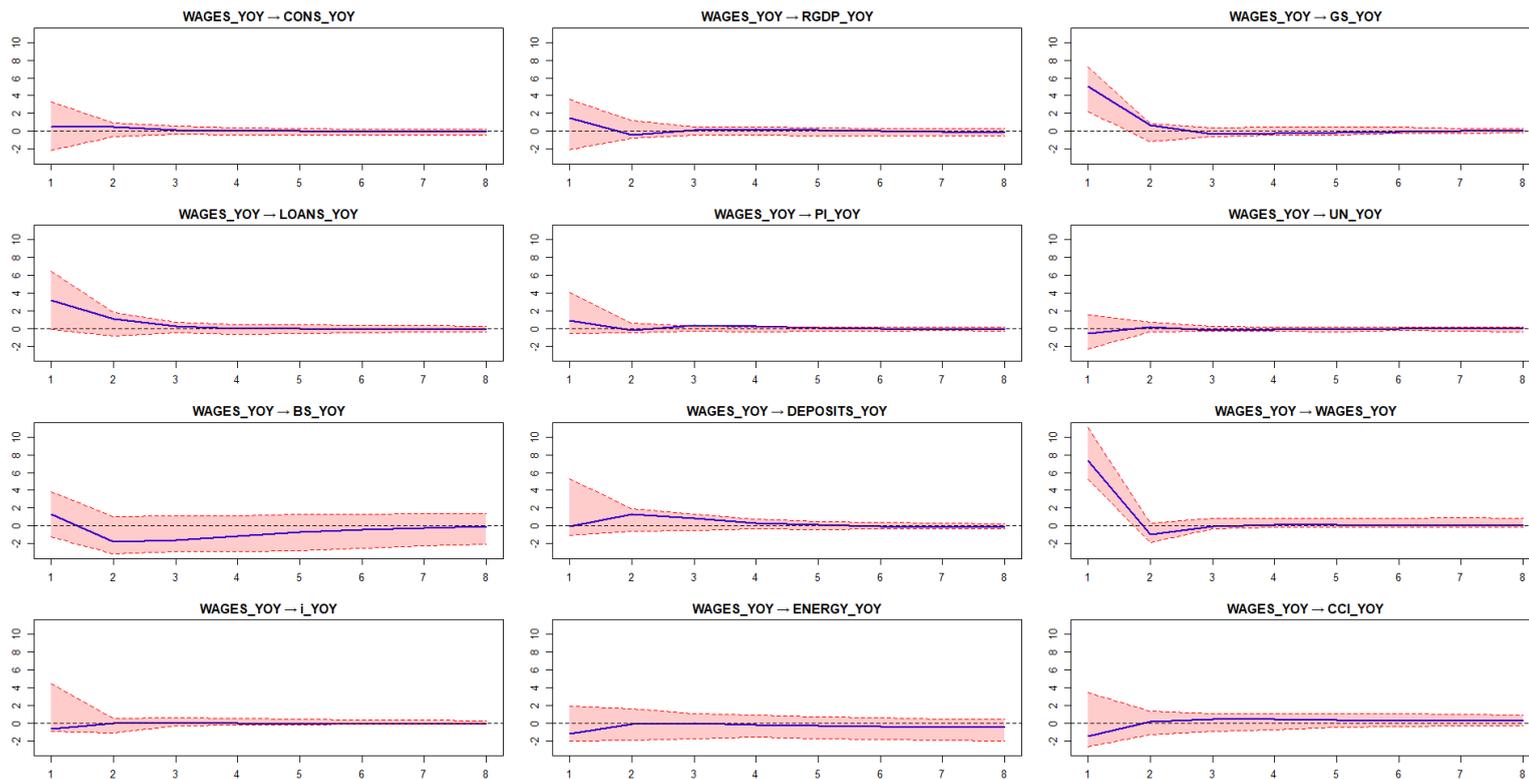


Figure 64. PVAR GMM system model impulse response functions when impulse is i_YOY . Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

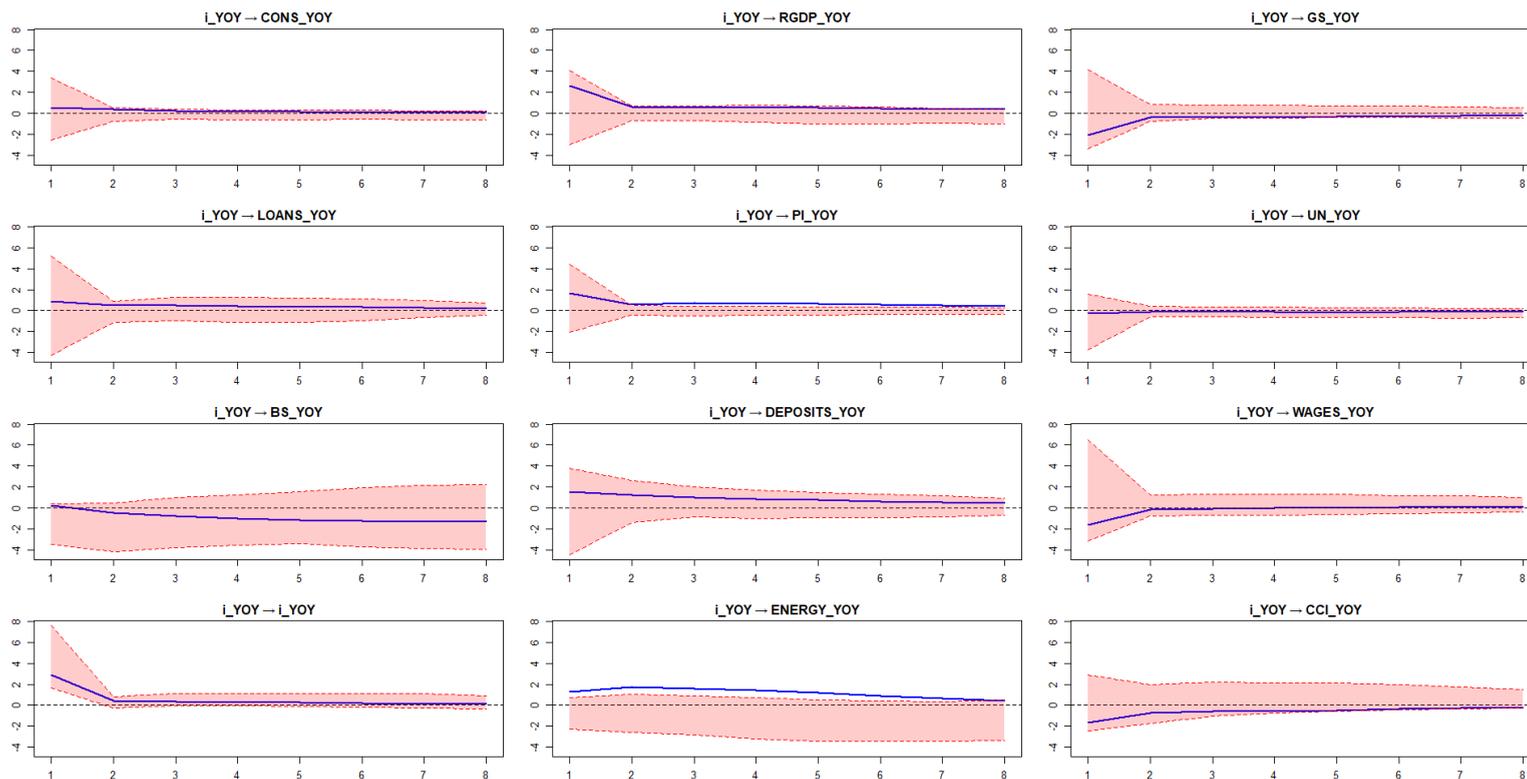


Figure 65. PVAR GMM system model impulse response functions when impulse is ENERGY_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

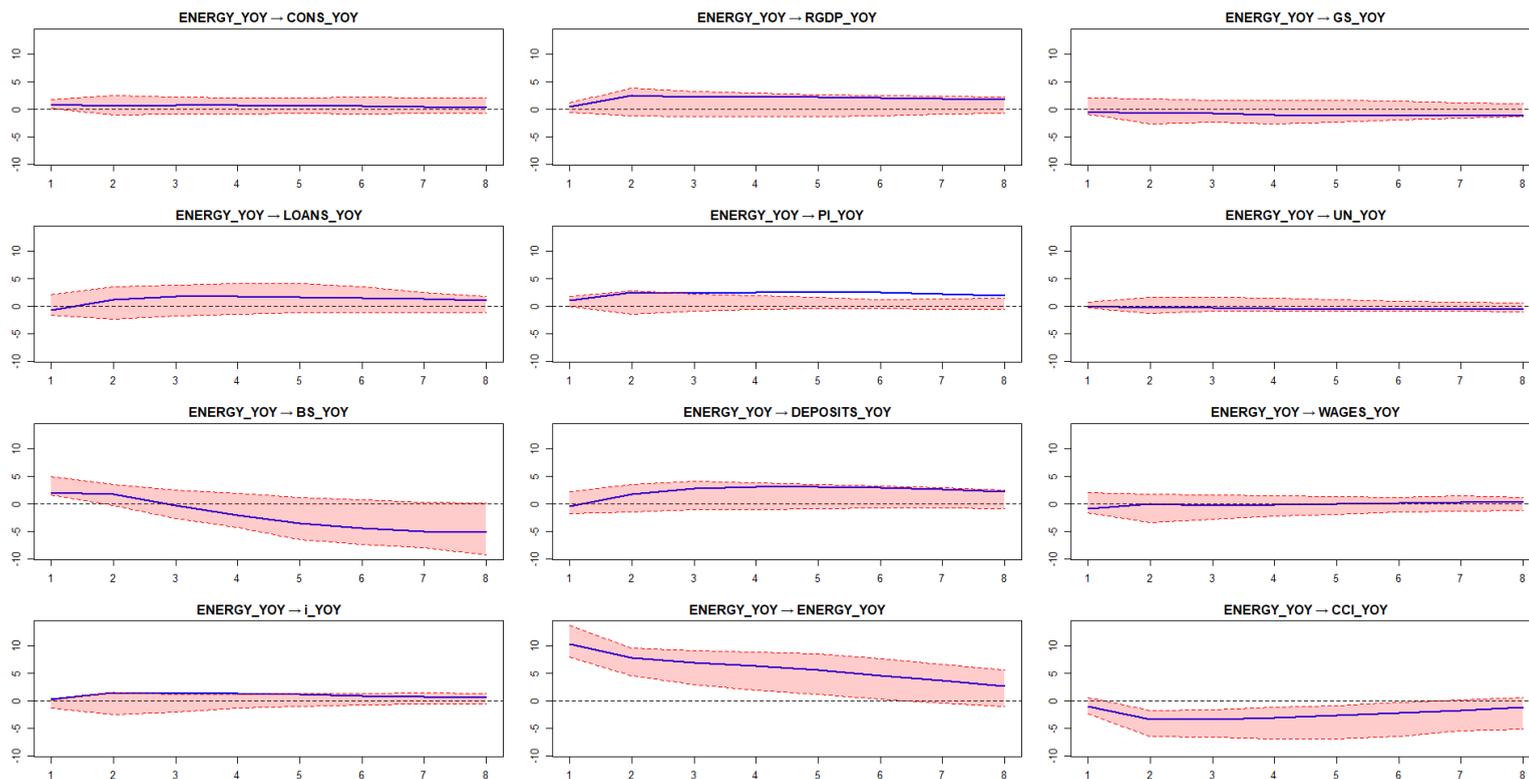


Figure 66. PVAR GMM system model impulse response functions when impulse is CCI_YOY. Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

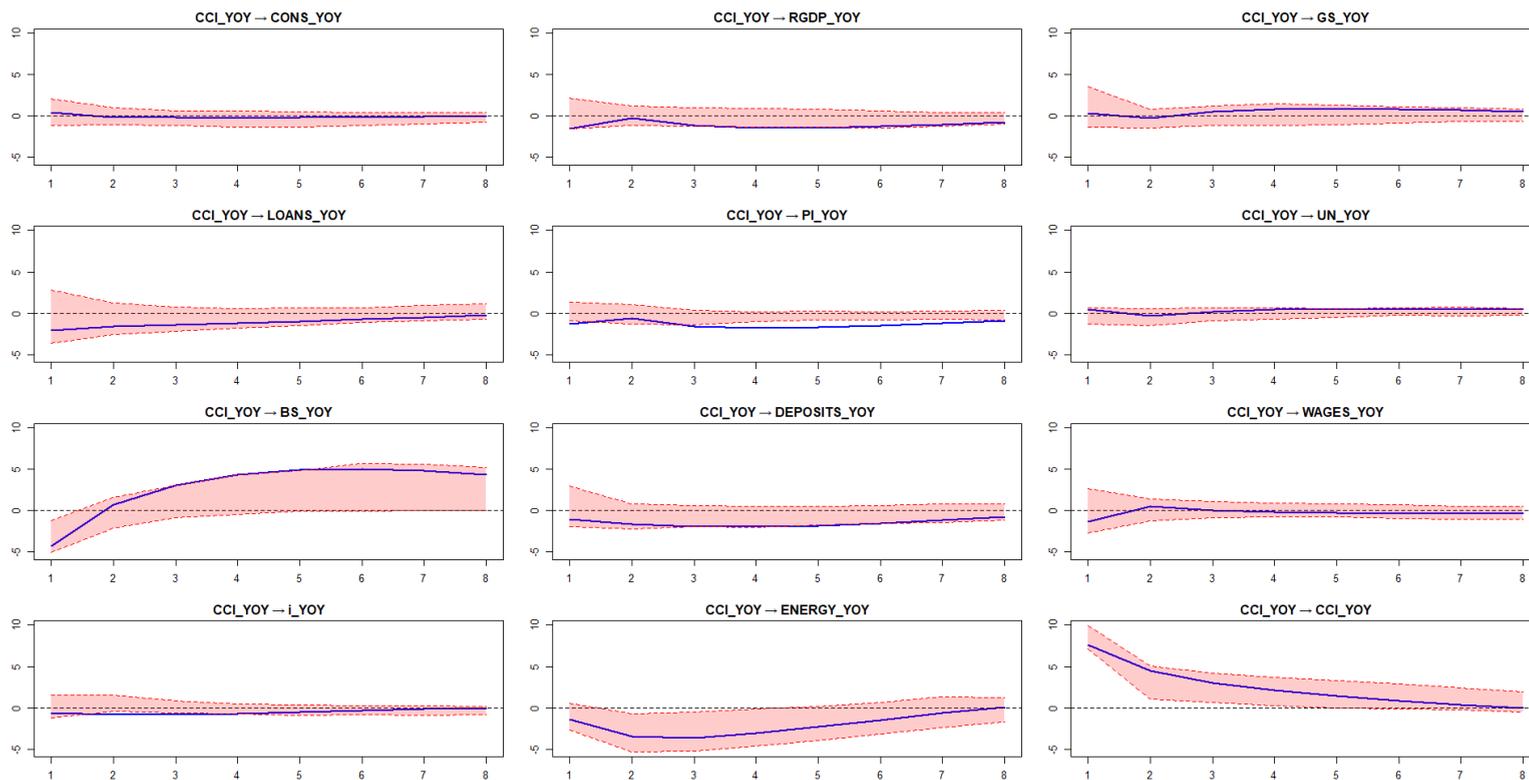


Figure 67. PVAR FE OLS model impulse response functions when impulse is PI_EXP1_YOY (quantified inflation expectations with scaling parameter as current inflation level). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

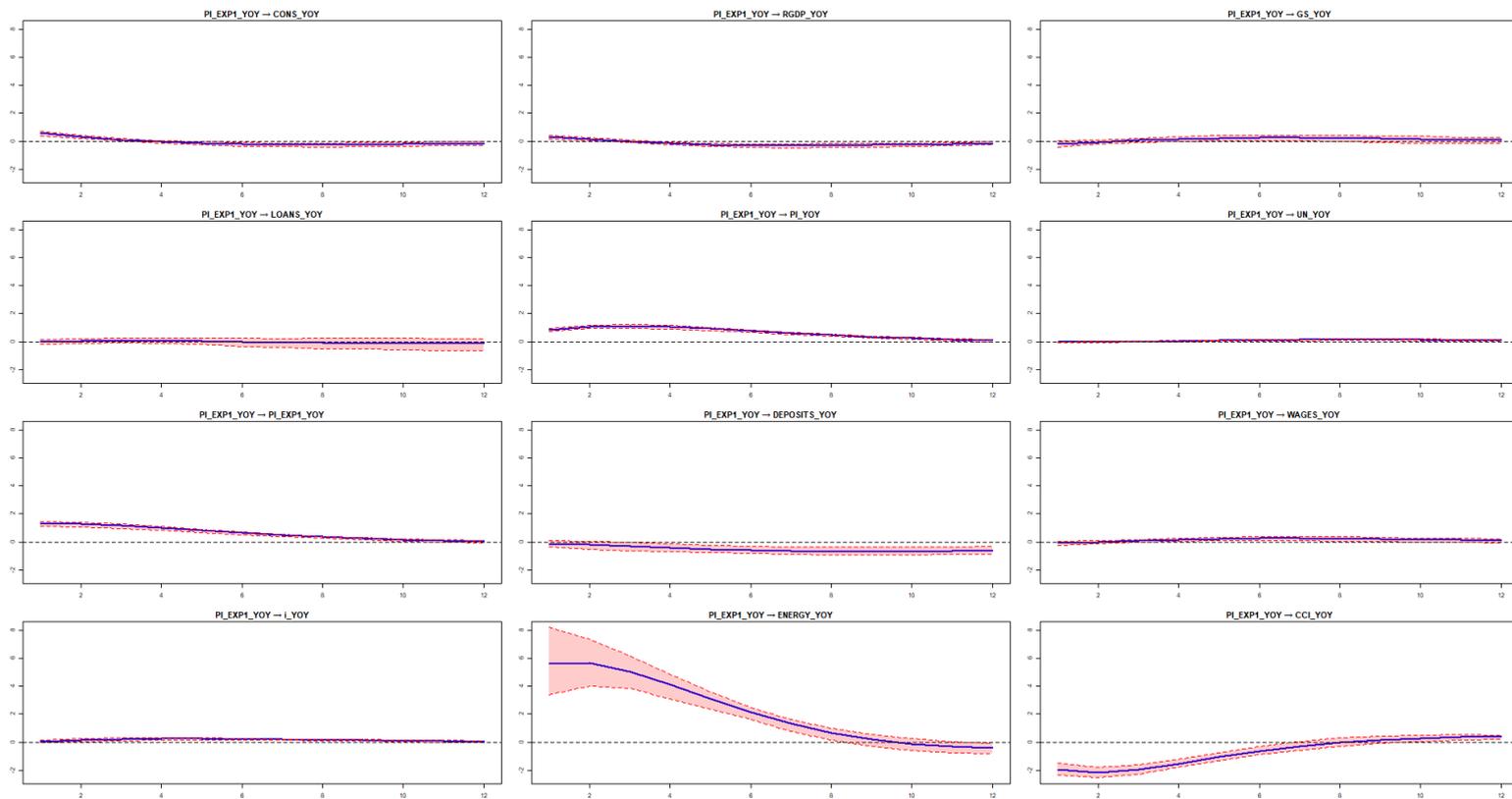


Figure 68. PVAR FE OLS model impulse response functions when response is PI_EXP1_YOY (quantified inflation expectations with scaling parameter as current inflation level). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

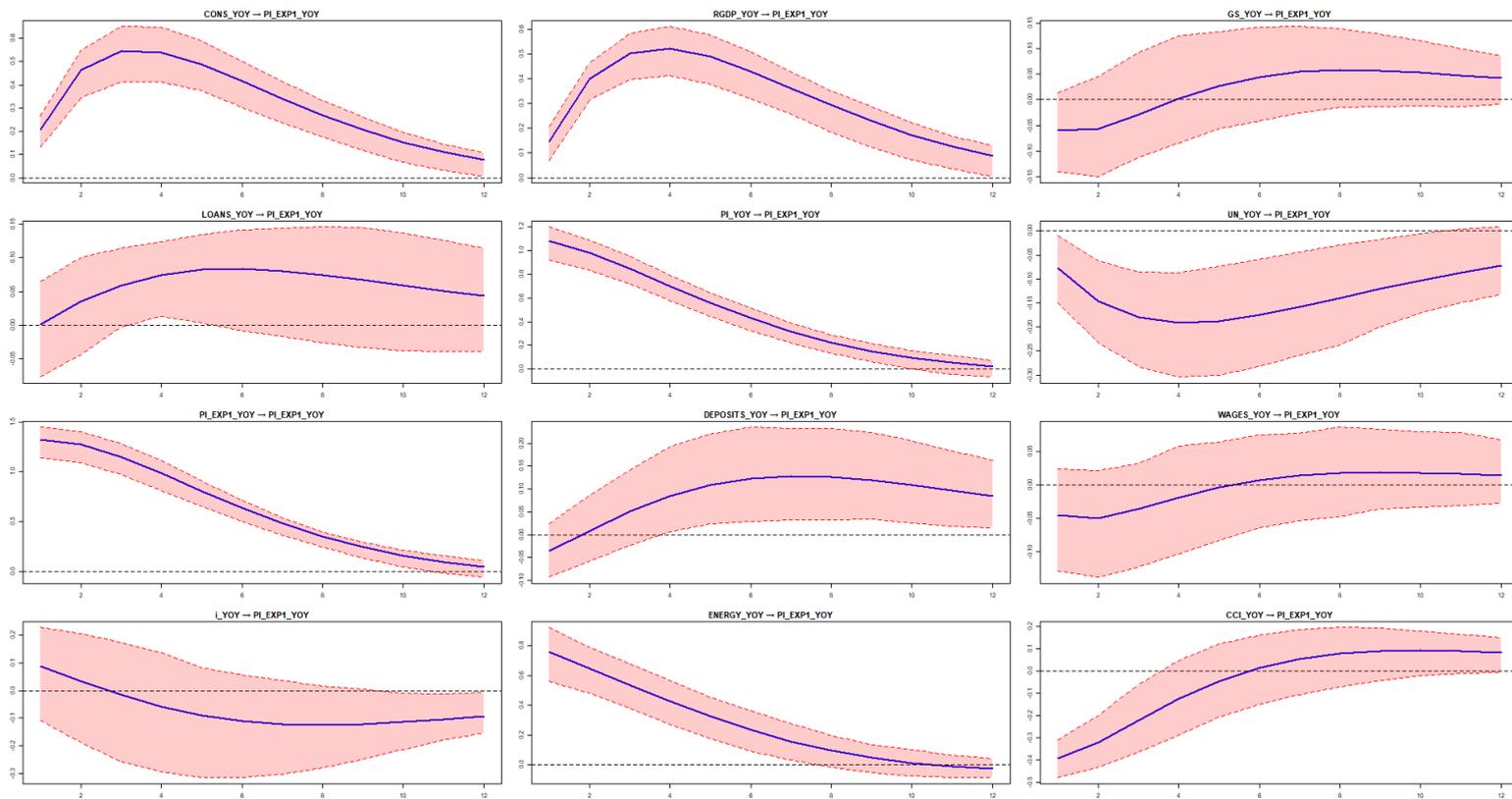


Figure 69. PVAR FE OLS model impulse response functions when impulse is PI_EXP2_YOY (quantified inflation expectations with scaling parameter as running average of past inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

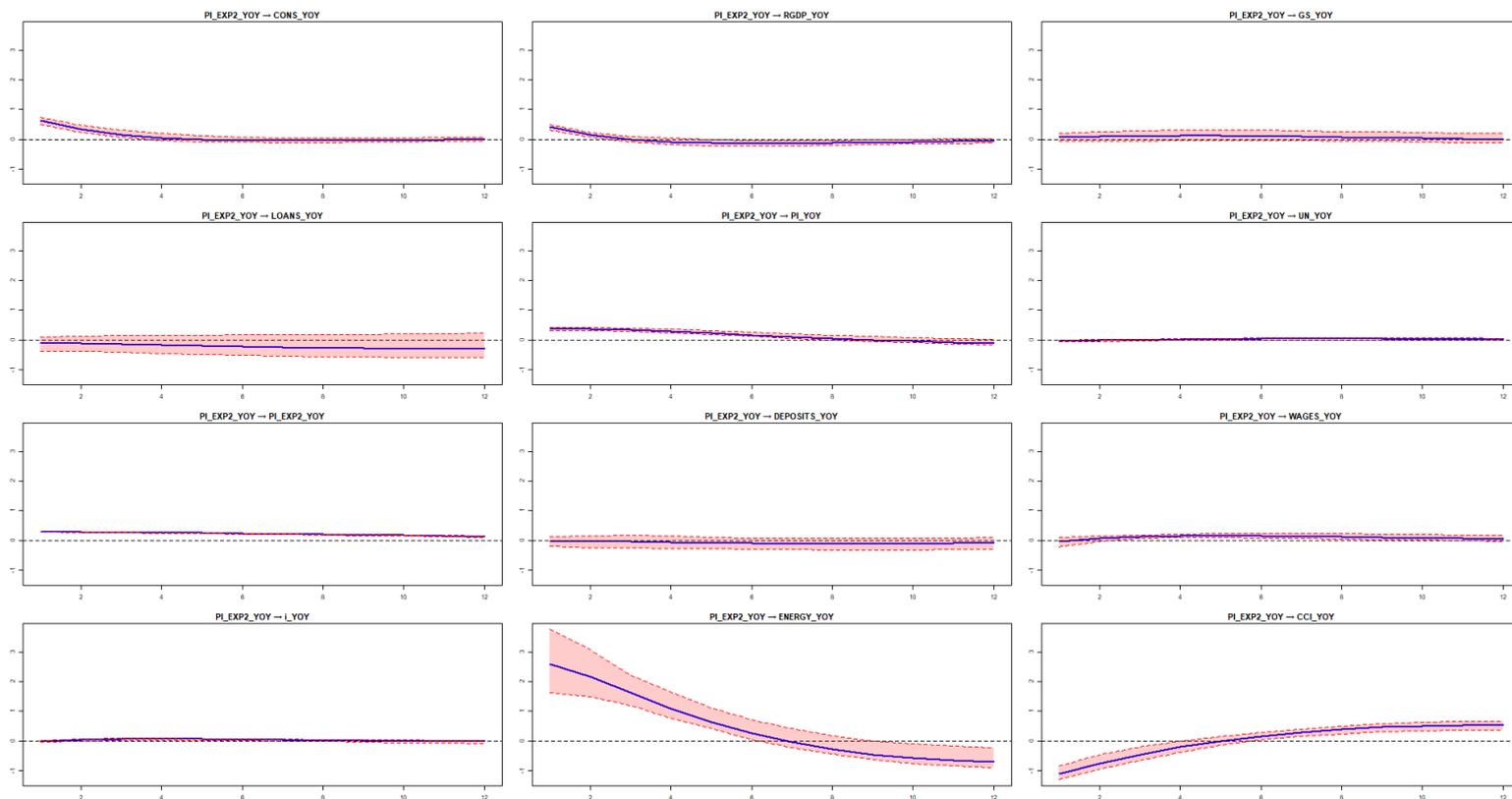


Figure 70. PVAR FE OLS model impulse response functions when response is PI_EXP2_YOY (quantified inflation expectations with scaling parameter as running average of past inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

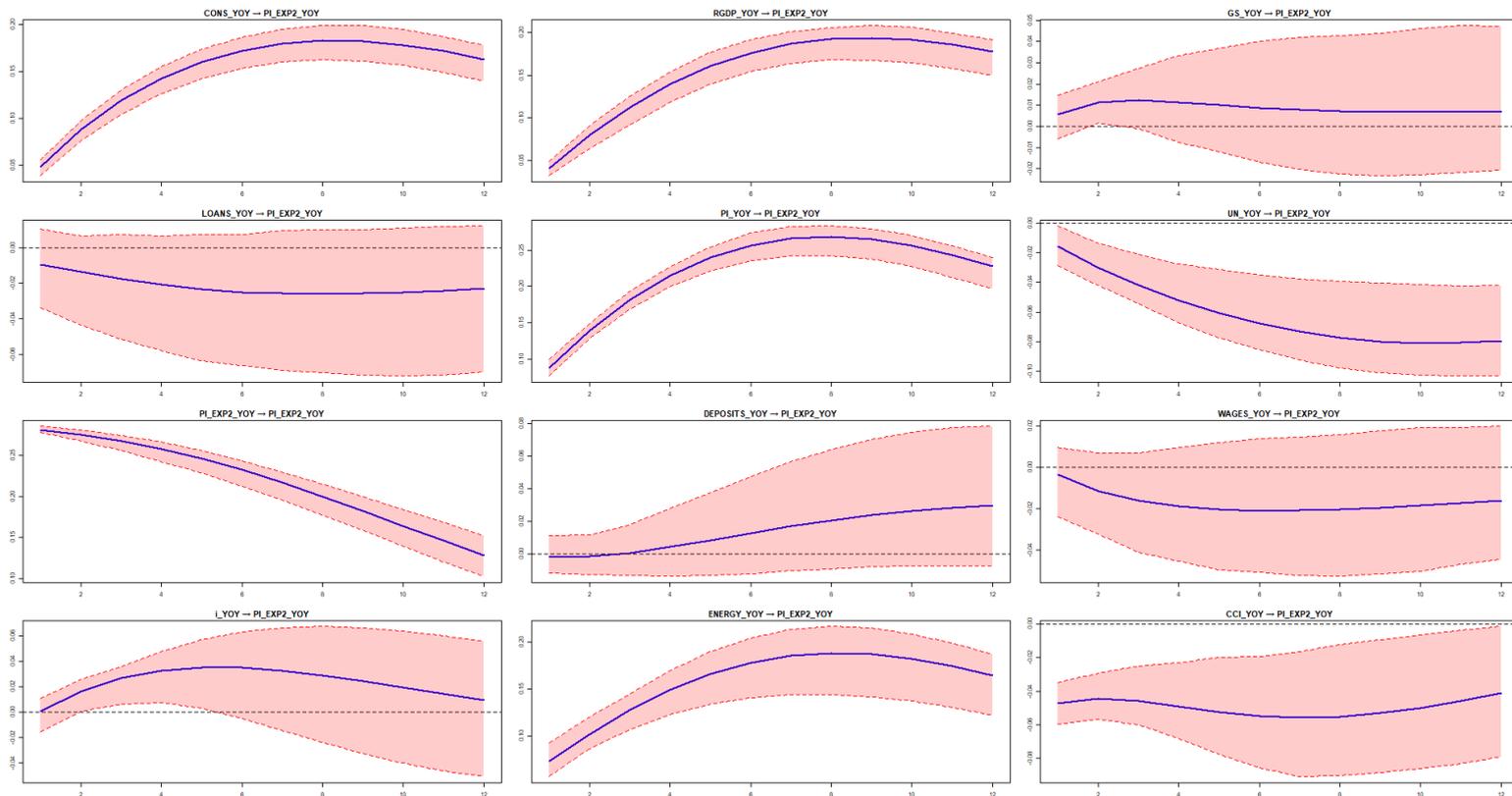


Figure 71. PVAR FE OLS model impulse response functions when impulse is PI_EXP3_YOY (quantified inflation with scaling parameter as quantified perceived inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

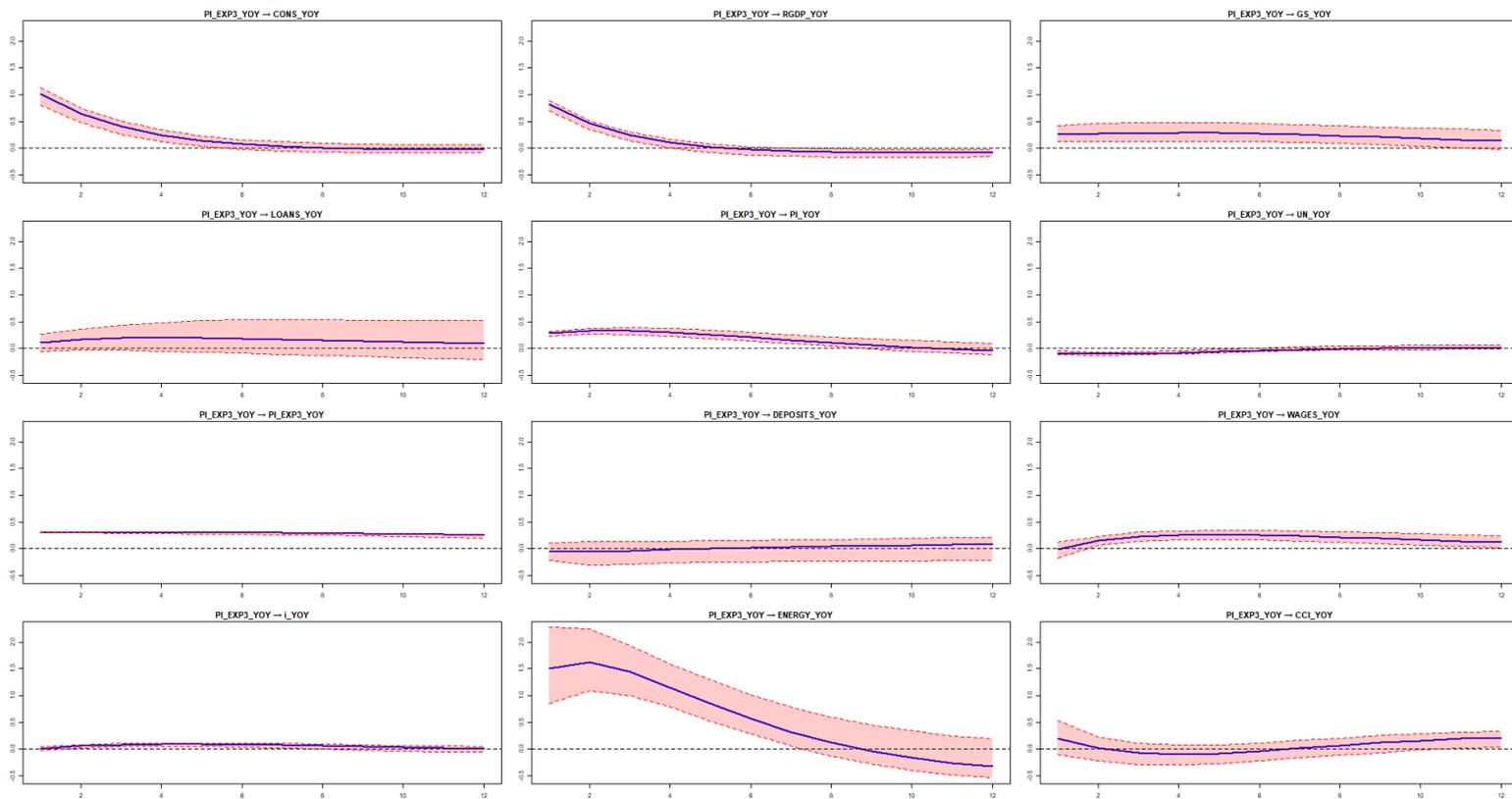


Figure 72. PVAR FE OLS model impulse response functions when response is PI_EXP3_YOY (quantified inflation expectations with scaling parameter as quantified perceived inflation). Blue solid line indicates general IRF, dashed red lines indicate bootstrapped 95% confidence interval.

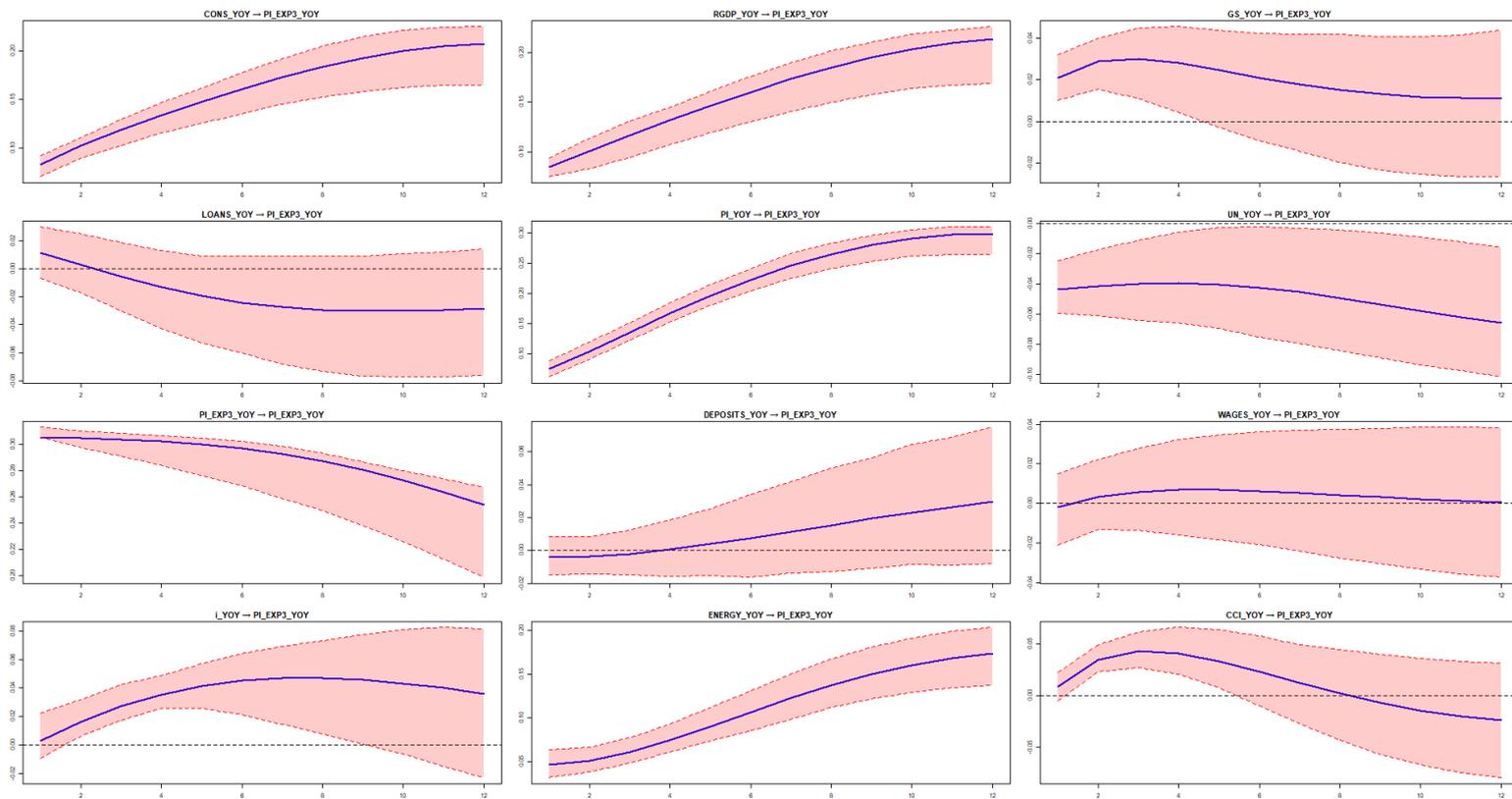


Figure 73. Forecast Error Variance Decomposition for real consumption YoY change (CONS_YOY), real GDP YoY change (RGDP_YOY), government spending YoY change (GS_YOY), household loans YoY change (LOANS_YOY).

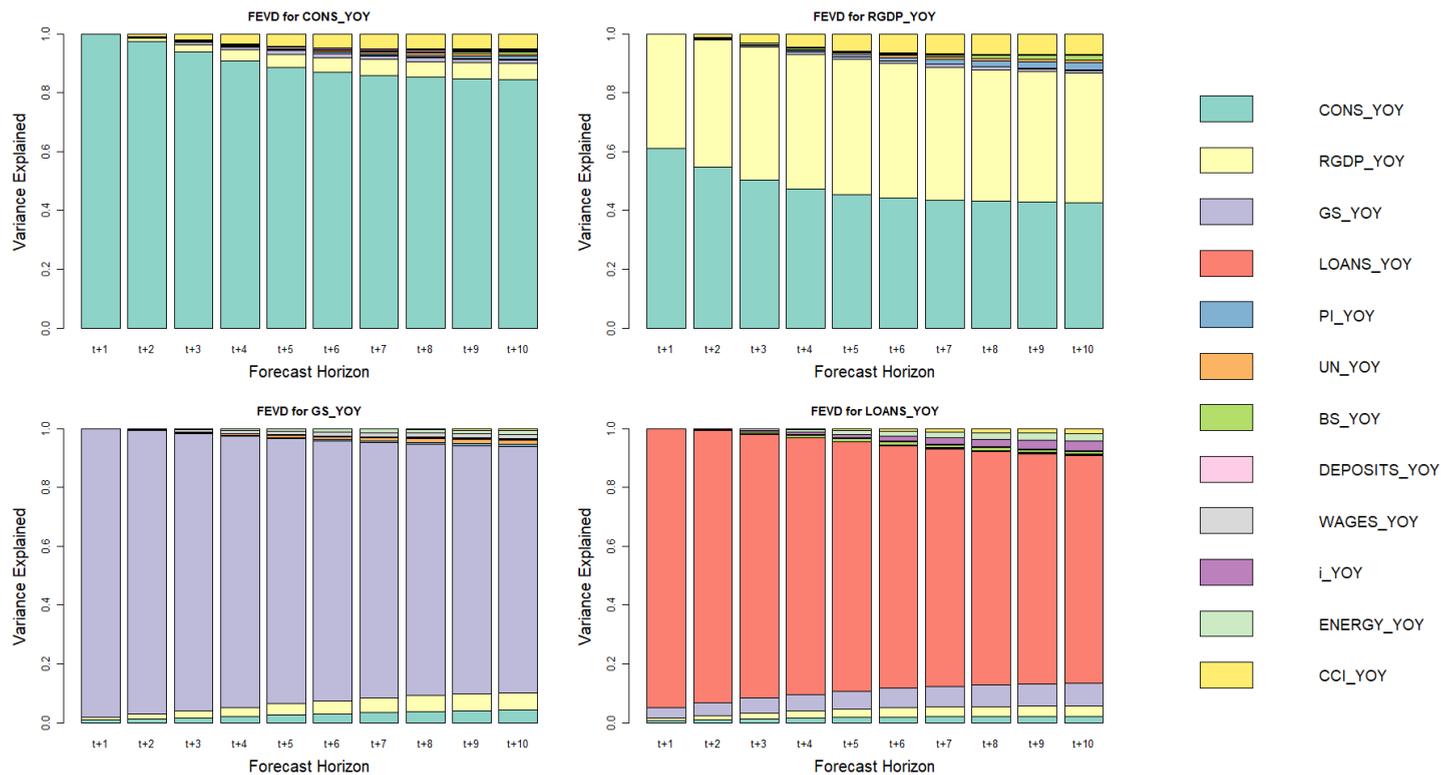


Figure 74. Forecast Error Variance Decomposition for YoY inflation (PI_YOY), unemployment rate YoY change (UN_YOY), balance statistics of consumer inflation expectations YoY change (BS_YOY), household deposits YoY change (DEPOSITS_YOY).

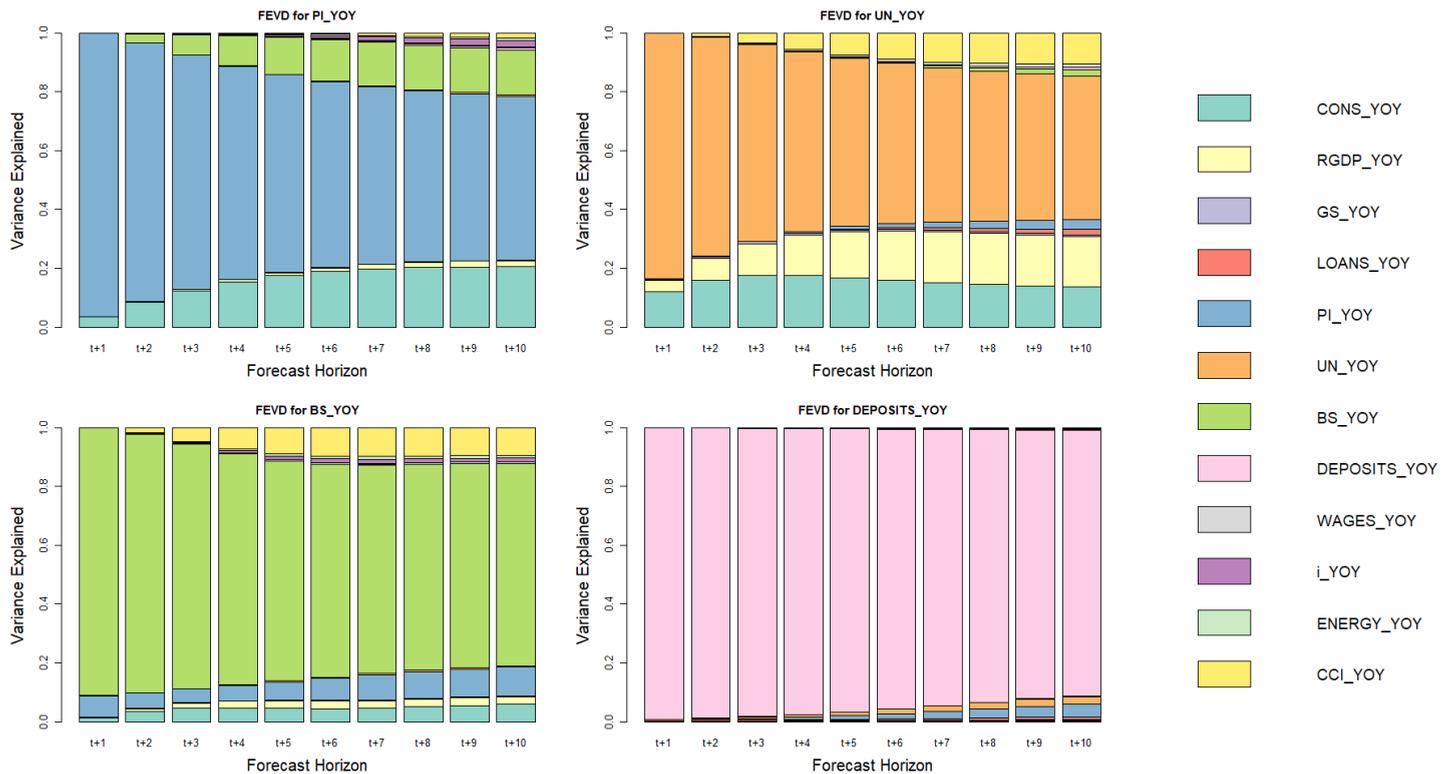
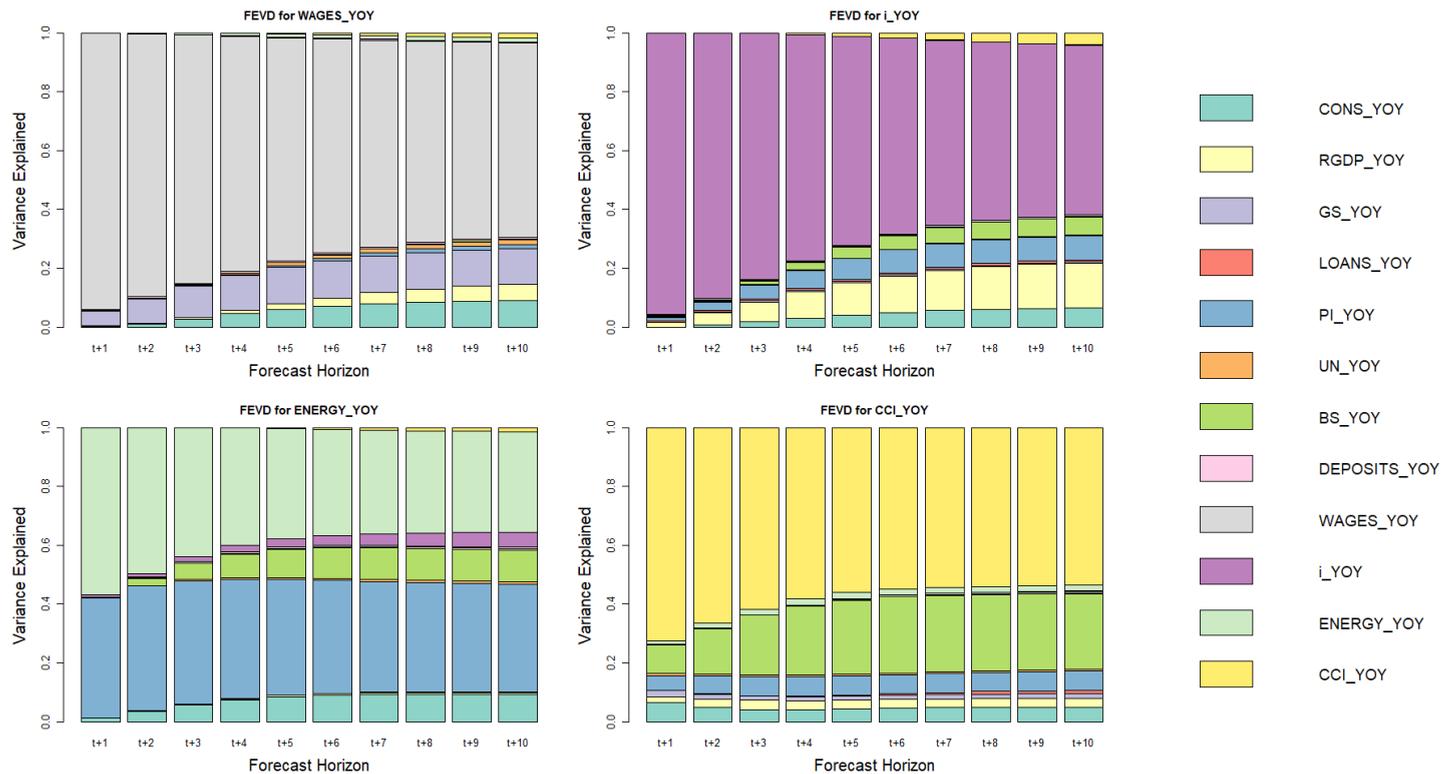


Figure 75. Forecast Error Variance Decomposition for wages YoY change (WAGES_YOY), interest rate YoY change (i_YOY), energy prices YoY change (ENERGY_YOY), consumer confidence index YoY change (CCI_YOY).



SANTRAUKA

ĮVADAS

Temos aktualumas. Infliacijos lūkesčių tyrimai pastaraisiais metais vėl tapo itin svarbūs makroekonominiuose tyrimuose ir ekonominės politikos diskusijose, ypač dėl po pandeminiu laikotarpiu stebėto infliacijos šuolio ir padidėjusio makroekonominio neapibrėžtumo. Infliacijos lūkesčiai atlieka esminį vaidmenį formuojant ekonominį elgesį, darydami įtaką namų ūkių vartojimo ir taupymo sprendimams, darbo užmokesčio deryboms bei įmonių kainodaros strategijoms. Kaip pabrėžiama tiek klasikiniuose, tiek šiuolaikiniuose makroekonominiuose modeliuose, infliacijos lūkesčiai yra vienas pagrindinių kanalų, per kuriuos pinigų politika veikia realius ekonominius rezultatus (Orphanides ir Williams, 2005; Woodford, 2003). Todėl infliacijos lūkesčių įtvirtinimas yra tapęs vienu pagrindinių centrinių bankų tikslų.

Nepaisant infliacijos lūkesčių teorinės svarbos, empiriniai rezultatai ir ekonominė, ypač vartotojų formuojamų infliacijos lūkesčių, reikšmė išlieka diskutuoti. Vis gausėjantys empiriniai tyrimai rodo, kad vartotojų infliacijos lūkesčiai dažnai yra šališki, labai heterogeniški ir menkai orientuoti į ateitį, o tai kelia abejonių dėl jų prognozinio tikslumo ir vaidmens makroekonominėje dinamikoje (Coibion ir Gorodnichenko, 2015; Rudd, 2021; Weber, Coibion ir Gorodnichenko, 2023). Naujausi tyrimai, paremti namų ūkių mikro-lygmens duomenimis ir atsitiktinių imčių tyrimais (angl. *randomized controlled trials*), taip pat rodo, kad infliacijos lūkesčiai stipriai reaguoja į ryškius kainų pokyčius, informacines intervencijas ir suvokiamos infliacijos neapibrėžtumą, tačiau išlieka tik iš dalies susieti su centrinių bankų tikslais (Duca, Kenny ir Reuter, 2021; Huber, Minina ir Schmidt, 2023; Kostyshyna ir Petersen, 2024). Tai rodo, kad infliacijos lūkesčių matavimo būdas yra neatsiejamas nuo jų interpretavimo ir naudojimo monetarinės ir fiskalinės politikos analizėje.

Vienas pagrindinių šios disertacijos elementų yra Carlson–Parkin (1975) metodo taikymas ir vertinimas. Carlson–Pakin (CP) metodas išlieka plačiausiai taikomas kokybinių apklausų duomenims apie infliacijos suvokimą ir lūkesčius paversti kiekybiniais įverčiais. Ilgalaiķ CP metodo patrauklumą lemia jo paprastumas ir galimybė generuoti laiko eilutes net tuomet, kai respondantai nurodo tik kainų pokyčių kryptį. Nepaisant to, platus metodo taikymas taip pat paskatino ir kritines diskusijas. CP metodu gautų įverčių pagrįstumas labai priklauso nuo prielaidų apie atsakymų skirstinio normalumą, nepastebimumo intervalų simetriškumą ir mastelio parametru pasirinkimą. Šios prielaidos, nors ir patogios, nėra neutralios – nukrypimai

nuo normalumo, vartotojų jautrumo kainoms pokyčiai ar heterogeniškumas tarp grupių gali iškraipyti gautus įverčius (Lolić ir Sorić, 2017; Rutkowska, Szyszko ir Pietrzak, 2023).

Standartinės Carlson–Parkin prielaidos gali būti nevysiškai tinkamos mažų ir atvirų Baltijos šalių ekonomikų kontekste. Šios ekonomikos yra labiau veikiamos išorinių kainų ir paklausos šokų, kurie gali lemti asimetrijas ar didesnę vartotojų infliacijos suvokimo sklaidą. Vartotojai taip pat gali suteikti didesnę svorį kainų didėjimui nei mažėjimui, todėl lūkesčių pasiskirstymas gali būti asimetriškas. Be to, struktūriniai pokyčiai, įskaitant euro įvedimą ir padidėjusios infliacijos laikotarpius, gali paveikti mastelio parametru stabilumą. Taip pat naujausi tarptautiniai tyrimai rodo, kad infliacijos lūkesčių formavimasis ir elgsena ryškiai skiriasi tarp šalių ir regionų, todėl iš didesnių euro zonos ekonomikų gautos išvados negali būti automatiškai taikomos kitoms šalims (Szyszko ir Rutkowska, 2019; Kliber ir kt., 2023). Tai savo ruožtu leidžia teigti, kad standartinių CP prielaidų taikymas Baltijos šalių kontekste reikalauja kruopštaus empirinio įvertinimo, kuris ir motyvuoja šioje disertacijoje atliekamą metodologinę analizę.

Šis tyrimas tiesiogiai nagrinėja ir siekia išspręsti minėtas metodologines problemas. Taikant CP metodą Baltijos šalių apklausų duomenims, tikrinamas šio metodo prielaidų patikimumas ekonomikose, kurios skiriasi nuo dažniausiai tiriamų didžiųjų euro zonos šalių. Be to, atsisakant griežtų pasiskirstymo prielaidų ir eksperimentuojant su alternatyviais mastelio parametrais, tyrimas prisideda prie metodologinės diskusijos apie tai, kaip geriausiai kiekybiškai įvertinti kokybinius apklausų atsakymus. Tokiu būdu sprendžiami du pagrindiniai iššūkiai, su kuriais susiduria tyrėjai ir pinigų politikos formuotojai: (1) palyginamų rodiklių tarp šalių poreikis ir (2) metodų pritaikymo konkrečiam nacionaliniam kontekstui svarba.

Problema ir tyrimo objektas. Pagrindinė disertacijoje nagrinėjama problema yra vartotojų infliacijos lūkesčių kiekybinio įvertinimo tikslumas, naudojant tikimybinis ir statistinius metodus. Carlson–Parkin metodas, plačiai taikomas kokybiniais apklausų atsakymams paversti kiekybiniais įverčiais, dažnai remiasi prielaida, kad vartotojų lūkesčiai yra normaliai pasiskirstę. Tačiau ankstesni tyrimai kvestionuoja šios prielaidos pagrįstumą, teigdami, kad alternatyvūs pasiskirstymai gali geriau atspindėti asimetrišką vartotojų lūkesčių pobūdį (Batchelor ir Orr, 1988; Lolić ir Sorić, 2017; Rutkowska, Szyszko ir Pietrzak, 2023). Todėl šio tyrimo objektas yra dvejopas. Pirma, siekiama kritiškai įvertinti CP metodu pagrįstų kiekybinimo metodų patikimumą, testuojant alternatyvias pasiskirstymo prielaidas, mastelio parametro pasirinkimus ir agregavimo procedūras. Tai apima vertinimą, ar metodologiniai patobulinimai pagerina lūkesčių atitikimą ir

prognozinę vertę tiek Baltijos šalyse, tiek platesnėje imtyje. Antra, siekiama išnagrinėti ekonominį vartotojų lūkesčių vaidmenį, įtraukiant kiekybinius įverčius į platesnius makroekonominis ryšius, įskaitant jų sąveiką su infliacija, vartojimu, nedarbu ir produkcija. Šis dvejetainis požiūris leidžia spręsti lūkesčių kiekybinimo metodologinius trūkumus (antras–penktas skyriai), empiriškai pritaikyti patobulintus metodus Baltijos šalims kaip nepakankamai ištirtoms ekonomikoms (trečias skyrius), patikrinti jų makroekonominę reikšmę ES masto paneliniuose duomenyse (ketvirtas skyrius) ir įtraukti socio-demografinį heterogeniškumą, siekiant didesnio sukiekybintų lūkesčių tikslumo (penktas skyrius). Tokiu būdu tyrimas prisideda tiek prie techninio lūkesčių matavimo tobulinimo, tiek prie empirinio supratimo gilinimo, tiriant kaip vartotojų lūkesčiai veikia infliacijos dinamiką ir yra jos veikiami skirtingose ekonominėse aplinkose.

Tyrimo tikslas ir uždaviniai. Pagrindinis šio tyrimo tikslas yra patikrinti infliacijos lūkesčių matavimo tikslumą ir pritaikomumą, tobulinant esamus kiekybinimo metodus ir nagrinėjant naujus požiūrius. Šis tikslas kyla iš poreikio suteikti politikos formuotojams patikimus duomenis apie vartotojų infliacijos lūkesčius, kurie yra būtini veiksmingai pinigų politikai įvairialypėje ekonominėje aplinkoje. Siekiant tyrimo tikslo, formuluojami šie uždaviniai:

1. Kritiškai įvertinti Carlson–Parkin metodo taikymą ir jo tradicinę normaliojo pasiskirstymo prielaidą, nagrinėjant alternatyvius statistinius pasiskirstymus (asimetriškus, leptokurtinius ir kt.), siekiant nustatyti, ar jie geriau atitinka vartotojų lūkesčių duomenis.

2. Ištirti euro įvedimo poveikį vartotojų infliacijos lūkesčių kiekybiniam vertinimui Baltijos šalyse ir nustatyti, ar perėjimas prie euro pakeitė optimalias kiekybinimo procedūras.

3. Patikrinti kiekybiškai įvertintų vartotojų infliacijos lūkesčių ir balanso statistikos orientaciją į ateitį bei prognozinę galią.

4. Išnagrinėti vartotojų lūkesčių makroekonominį vaidmenį Europos Sąjungoje, taikant panelinį VAR modelį 26 ES šalims ir patikrinti kaip modelio rezultatus paveikia skirtingos CP metodo konfigūracijos.

5. Ištirti infliacijos lūkesčių heterogeniškumą tarp skirtingų socio-demografinių grupių, analizuojant atsakymus pagal amžių, pajamas, išsilavinimą ir lytį bei vertinant, ar grupėms pritaikytas kiekybinimas pagerina tikslumą.

Tyrimo metodai. Šio tyrimo metodologija remiasi Carlson–Parkin (CP) metodo taikymu ir tobulinimu, siekiant kokybinius apklausų atsakymus paversti kiekybiniais infliacijos lūkesčių rodikliais. Nors tradicinė CP metodologija daro prielaidą apie normalų atsakymų pasiskirstymą, šiame tyrime vertinamas jos patikimumas, testuojant alternatyvias pasiskirstymo

formas, įskaitant asimetriškus ir leptokurtinius pasiskirstymus, bei analizuojant skirtingų mastelio parametrų poveikį. Šie patobulinimai leidžia lankstesnę vartotojų lūkesčių vertinimą, ypač tais atvejais, kai įprastos prielaidos nėra pagrįstos. Greta pagrindinio metodo, tyrime taikomi ir papildomi metodai. Pirmame, antrame ir trečiame skyriuose atliekama sisteminė mokslinės literatūros apžvalga, naudojama aprašomoji statistika, grafinė analizė ir vienietinės šaknies testai, siekiant įvertinti CP metodo reikšmę ir jo empirines savybes platesniame lūkesčių matavimo kontekste. Paprastųjų mažiausių kvadratų regresijos taikomos kiekybiškai įvertintų lūkesčių prognoziniam tikslumui palyginti su faktine infliacija. Ketvirtame skyriuje, analizuojant dvidešimt šešias ES šalis, taikomas panelinis vektorinės autoregresijos (PVAR) modelis, leidžiantis ištirti vartotojų lūkesčių sąveiką su infliacija, BVP, nedarbu ir vartojimu. Penktame skyriuje metodologija išplečiama taikant grupėmis pagrįstą infliacijos lūkesčių kiekybinimą, apklausų atsakymai išskaidomi pagal amžių, pajamas, išsilavinimą ir lytį, CP metodas taikomas kiekvienai grupei atskirai, o vėliau rezultatai agreguojami naudojant populiacijos svorius.

Tyrimo reikšmė, naujumas ir indėlis. Ši disertacija prisideda prie infliacijos lūkesčių problematiką nagrinėjančio mokslinio diskurso keliais tarpusavyje susijusiais aspektais. Pirmia, ji kvestionuoja įprastą normaliojo pasiskirstymo prielaidą Carlson–Parkin metode, sistemingai testuodama alternatyvias pasiskirstymo formas ir mastelio parametrus. Nors CP metodas plačiai taikomas tarptautiniuose duomenų rinkiniuose, tik nedaugelis tyrimų nagrinėjo jo patikimumą mažose ir atvirose ekonomikose (Berk, 1999; Lyziak, 2003 ir kt.), o detalus alternatyvių specifikacijų lyginimas empiriniuose tyrimuose atliekamas dar rečiau (Lolić ir Sorić, 2017; Rutkowska, Szyszko ir Pietrzak, 2023). Siekiant patobulinti metodologiją ir parodyti, kaip kiekybiniai įverčiai priklauso nuo modelio pasirinkimų, tyrimas prisideda prie diskusijos, nagrinėjančios kaip geriausiai konvertuoti informaciją iš kokybinių apklausų. Antra, disertacija pateikia naujų empirinių įrodymų iš Baltijos šalių – Lietuvos, Latvijos ir Estijos, kurios dažnai nepakankamai atstovaujamos tarptautiniuose tyrimuose. Trečia, tyrimas išplečia analizę į platesnį Europos kontekstą, taikant panelinį VAR modelį dvidešimt šešioms ES šalims. Šio tyrimo naujumas glūdi ne pačiame ekonometriniame metode, o vartotojų lūkesčių įtraukimo būde. Kiekybiškai įvertinus apklausų duomenis, naudojant skirtingas CP metodo specifikacijas ir palyginus jas su balansų statistika, parodoma, kaip metodologiniai sprendimai keičia įvertintą lūkesčių makroekonominį vaidmenį. Gauti rezultatai atskleidžia reikšmingą tarp-šalinį heterogeniškumą ir patvirtina, kad nors vartotojų lūkesčiai gali turėti sąryšį su vartojimu ir infliacija, jų poveikis

yra nevienodas ir gauti rezultatai priklauso nuo matavimo būdo. Galiausiai, tyrime įtraukiamas heterogeniškumas, analizuojant lūkesčius pagal amžių, pajamas, išsilavinimą ir lytį. Šis grupėmis pagrįstas požiūris parodo, kad išskaidytas kiekybinimas gali reikšmingai pagerinti vertinimo tikslumą ir suteikti įžvalgų apie demografinių veiksnių vaidmenį formuojant infliacijos suvokimą ir lūkesčius.

Praktinė reikšmė. Šis tyrimas reikšmingas analizuojant praktinę galimybę pagerinti vartotojų infliacijos lūkesčių matavimą ir interpretavimą formuojant pinigų politiką. Nustatant, kurie kiekybinimo metodai ir jų konfigūracijos suteikia tiksliausius rezultatus, disertacija pateikia gaires centriniams bankams ir statistikos institucijoms, kurios remiasi apklausomis pagrįstais rodikliais. Pabrėžiama, kad rezultatai yra jautrūs pasiskirstymo prielaidoms, mastelio parametrams ir agregavimo taisyklėms, todėl politikos formuotojai turėtų vertinti kiekybinius lūkesčių rodiklius kaip informatyvius, bet nuo metodo priklausomus indikatorius, o ne objektyvias reikšmes.

Ginamieji teiginiai:

1. Tradicinė prielaida, kad vartotojų lūkesčiai Carlson–Parkin metode yra normaliai pasiskirstę, nėra universaliai pagrįsta. Alternatyvios pasiskirstymo formos gali užtikrinti tikslesnį infliacijos lūkesčių kiekybinį įvertinimą, mastelio parametro pasirinkimas turi didesnę reikšmę įverčių tikslumui.

2. Kiekybiškai įvertinti vartotojų infliacijos lūkesčiai pasižymi ribotu orientavimu į ateitį ir prognozinio tikslumu, tačiau jie geriau nei balansų statistika paaškina būsimos infliacijos dinamiką.

3. Vartotojų infliacijos lūkesčiai yra susiję su išmatuojamais makroekonominiais pokyčiais, konkrečiai – vartojimu, nedarbu ir infliacija, Europos Sąjungoje, panelinio VAR modelio kontekste.

4. Metodologiniai sprendimai, priimami kiekybiškai vertinant kokybinius apklausų duomenis – pasiskirstymo prielaidos, mastelio parametrai ir agregavimo taisyklės – turi esminės įtakos tiek akademiniam tyrimams, tiek pinigų politikai, nes formuoja įvertintą lūkesčių vaidmenį ekonominiuose rezultatuose.

5. Socio-demografinio heterogeniškumo įtraukimas į infliacijos lūkesčių ar suvokimo kiekybinimą reikšmingai pagerina tikslumą ir atskleidžia sistemingus skirtumus tarp amžiaus, pajamų, išsilavinimo ir lyties grupių.

Disertacijos struktūra. Disertaciją sudaro penki skyriai. Pirmajame skyriuje apžvelgiama teorinė ir empirinė infliacijos lūkesčių problematiką nagrinėjanti literatūra, antrajame – kiekybinimo metodologija, ypatingą

dėmesį skiriant Carlson–Parkin metodui ir jo alternatyvoms. Trečiajame skyriuje šie metodai taikomi Baltijos šalims, analizuojant vartotojų lūkesčius, orientavimąsi į ateitį ir prognozinį tikslumą. Ketvirtajame skyriuje analizė išplečiama iki dvidešimt šešių ES šalių, taikant panelinį VAR modelį ir vertinant vartotojų lūkesčių makroekonominį vaidmenį bei CP metodo taikymo poveikį rezultatams. Penktajame skyriuje nagrinėjamas demografinis heterogeniškumas, parodant, kaip grupėmis pagrįstas kiekybinimas pagerina matavimo tikslumą.

1. INFLIACIJOS LŪKESČIŲ TEORINIS PAGRINDAS IR LITERATŪROS APŽVALGA

Kadangi infliacijos lūkesčiai atlieka centrinį vaidmenį šiuolaikinėje makroekonomikoje, tačiau juos sunku tiesiogiai stebėti ir kiekybiškai įvertinti, mokslinis diskursas šia tema yra itin platus ir nevienareikšmis. Todėl šiame skyriuje apžvelgiama infliacijos lūkesčių sampratos raida ekonominėje teorijoje – nuo ankstyvųjų keinsistinių ir adaptyvių modeliavimo mechanizmų iki racionalių ir riboto racionalumo mechanizmų. Taip pat apžvelgiami pagrindiniai infliacijos lūkesčių matavimo būdai, ypatingą dėmesį skiriant kiekvieno jų stiprybėms ir ribotumams. Galiausiai skyriuje aptariamos metodologinės diskusijos dėl kiekybinimo technikų, ypač Carlson–Parkin metodo, siekiant identifikuoti neišspręstus klausimus, kurie motyvuoja šios disertacijos empirinius ir metodologinius indėlius. Diskusija struktūruojama taip, kad išryškintų literatūros kryptis, kurios yra svarbiausios vartotojų infliacijos lūkesčiams ir kokybinių apklausų duomenų kiekybinimui.

1.1. Infliacijos lūkesčių vaidmuo ekonominėje teorijoje

Ankstyvieji klasikiniai ir neoklasikiniai ekonomikos modeliai infliacijos lūkesčių vaidmeniui skyrė ribotą dėmesį, remdamiesi prielaida, kad rinkos yra savireguliuojančios, o ekonominiai agentai disponuoja visa reikalinga informacija ir geba tiksliai numatyti ateitį. Tačiau, didėjant ekonominiam neapibrėžtumui šios prielaidos tapo vis mažiau įtikinamos ir XX a. viduryje buvo pradėta iš naujo vertinti lūkesčių reikšmė. Esminį lūžį pažymėjo John M. Keynes (1936), kuris pabrėžė, kad neapibrėžtomis sąlygomis ekonominių agentų elgseną lemia ne mechaninės taisyklės, o subjektyvūs lūkesčiai ir psichologiniai veiksniai, vadinami *gyvuliškaisiais instinktais*. Keynes'o požiūriu, būtent lūkesčiai skatina investicijų svyravimus ir formuoja ekonominius ciklus, todėl tampa centriniu makroekonominės analizės

elementu. Ilgainiui mokslinėje literatūroje išsiskyrė trys pagrindinės infliacijos lūkesčių formavimosi kryptys.

Adaptyvių lūkesčių teorija, remiantis P. Cagan (1956), teigia, kad ekonominiai agentai formuoja būsimus infliacijos lūkesčius, remdamiesi praeities patirtimi ir palaipsniui juos koreguoja, reaguodami į ankstesnių prognozių klaidas. Šis požiūris buvo plačiai taikomas ankstyvuosiuose Phillips kreivės modeliuose, tačiau vėliau susilaukė kritikos. M. Friedman (1968) ir E. Phelps (1967) parodė, kad ignoruojant lūkesčių poveikį neįmanoma paaiškinti ilgalaikio infliacijos ir nedarbo ryšio bei stagflicijos reiškinio. Taigi, nors adaptyvūs infliacijos lūkesčiai gali paaiškinti trumpalaikius prisitaikymus, jų ribotumas išryškėja ilgajame laikotarpyje, nes pastarieji pernelyg remiasi istorine informacija.

Šią kritiką išplėtojo **racionalių lūkesčių** teorija, kurią suformulavo J. Muth (1961) ir išpopuliarino naujosios klasikinės minties atstovai. Pagal racionalių lūkesčių hipotezę, ekonominiai agentai naudoja visą prieinamą informaciją ir nedaro sisteminių prognozavimo klaidų. Anot R. Lucas (1976), ekonominiai modeliai, neatsižvelgiantys į lūkesčių pokyčius, negali patikimai vertinti ekonominės politikos poveikio (Lucas kritika). Tai lėmė išvadą, jog sisteminga pinigų politika turi ribotą poveikį realiems ekonominiams kintamiesiems, nes agentai ją numato. Vis dėlto, racionalių lūkesčių teorija buvo kritikuojama dėl pernelyg stiprios racionalumo ir pilnos informacijos prielaidos.

Atliepiant šias problemas, išsivystė **neracionalių arba riboto racionalumo lūkesčių** modeliai. H. Simon (1955) teigė, kad individų kognityviniai gebėjimai ir informacijos apdorojimo galimybės yra ribotos, todėl jų sprendimai dažnai grindžiami euristika, o ne optimizacija. Elgsenos ekonomikos tyrimai (Kahneman ir Tversky, 1979; Shiller, 2000) papildė šį požiūrį, parodydami, kad lūkesčius veikia sisteminiai šališkumai, tokie kaip *bandos elgsena*, nuostolių vengimas ar per didelis pasitikėjimas. Be to, nepilnos informacijos modeliai (Mankiw ir Reis, 2002) ir politikos formuotojų informacijos apribojimai (Orphanides, 2001) atskleidė, kad tiek privatūs ekonominiai agentai, tiek institucijos gali formuoti netikslius infliacijos lūkesčius. Taigi šios kryptys suteikia realesnį lūkesčių formavimosi vaizdą ir yra ypač aktualios analizuojant vartotojų infliacijos lūkesčius.

1.2 Infliacijos lūkesčių matavimas ir poveikis

Šiame poskyryje apžvelgiama, kaip matuojami infliacijos lūkesčiai tarp skirtingų agentų ir kokios esminės diskusijos kyla moksliniame diskurse.

1.2.1 Infliacijos lūkesčių svarba

Šiuolaikiniuose makroekonominiuose modeliuose infliacijos lūkesčiai laikomi esmine ekonominių rezultatų formavimo dalimi ir yra įtraukiami į tokius modelius kaip Phillips kreivė. Infliacijos lūkesčiai pripažįstami kaip turintys reikšmingą įtaką plačiam ekonominių sprendimų spektrui, ypač pinigų politikos planavimo kontekste, kur infliacijos lūkesčiai gali tiek veikti, tiek būti veikiami ekonominių agentų elgsenos. Infliacijos lūkesčių svarbos argumentas grindžiamas jų savaiminio išsipildymo pobūdžiu, t. y. jei agentai tikisi didesnės infliacijos, jie gali keisti elgseną taip, kad prisidėtų prie faktinio infliacijos didėjimo. Šis savaime išsipildančios pranašystės principas iliustruojamas ir sąryšyje tarp darbo užmokesčio ir infliacijos. Remiantis šiuo principu, įmonės, numatydamos sąnaudų augimą, gali iš anksto didinti kainas, o darbuotojai, tikėdamiesi pragyvenimo kaštų augimo, gali reikalauti didesnių atlyginimų, kad išlaikytų perkamąją galią. Tai reiškia, kad infliacijos lūkesčiai paskatina agentus imtis prevencinių veiksmų, kurie sukuria realų infliacinį procesą, patvirtina pirminius lūkesčius ir suformuoja grįžtamąjį ryšį. Dėl šios priežasties infliacijos lūkesčių valdymas arba įtvirtinimas yra laikomas vienu svarbiausių centrinių bankų uždavinių, užtikrinant veiksmingą pinigų politiką. Kaip pažymi B. S. Bernanke (2007), kai infliacijos lūkesčiai yra gerai įtvirtinti, ekonominiai agentai pasitiki, kad centrinis bankas ilgainiui užtikrins kainų stabilumą, o šis pasitikėjimas padeda išvengti pernelyg didelio infliacijos rodiklių nepastovumo. Priešingai, jei lūkesčiai nėra gerai įtvirtinti, tai gali reikšmingai destabilizuoti ekonominę aplinką, taip paskatinant infliacinius arba defliacinius procesus. Taigi siekdami mažinti rinkos svyravimus ir stabilizuoti infliaciją, centriniai bankai stengiasi veikti agentų elgseną, formuodami lūkesčius per komunikaciją ir politikos pranešimus, t. y. taikydami išankstinį orientavimą (angl. *forward guidance*) (Woodford, 2003; Blinder, Ehrmann, Fratzscher, De Haan ir Jansen, 2008). Atitinkamai, sudėtingiausias pinigų politikos formuotojų uždavinys yra užtikrinti, kad infliacijos lūkesčiai išliktų gerai įtvirtinti, nepaisant trumpalaikių svyravimų ar ekonominio neapibrėžtumo. Todėl infliacijos lūkesčių matavimas padeda centriniam bankams tiksliau prognozuoti būsimą infliacijos trajektoriją ir palaikyti ilgalaikį ekonominį stabilumą.

1.2.2. Skirtingų infliacijos lūkesčių tipų matavimas

Finansų rinkų infliacijos lūkesčiai. Rinkos infliacijos lūkesčiai atspindi finansų rinkų numatomą infliacijos lygį ir yra išvedami iš infliacijai indeksuotų obligacijų bei išvestinių finansinių priemonių kainų. Dažniausiai naudojami rodikliai yra infliacijos lūkesčių skirtumas (angl. *breakeven inflation rate*, BEIR) ir infliacijos apsikeitimo sandoriai. BEIR parodo vidutinį metinį infliacijos lygį, kurio tikisi investuotojai per obligacijos galiojimo laikotarpį, ir yra apskaičiuojamas kaip nominalių ir infliacijai indeksuotų obligacijų pajamingumo skirtumas. Tokiu būdu infliacijos lūkesčiai atspindi investuotojų elgsenoje, kai tikintis didesnės infliacijos reikalaujama didesnio nominalių obligacijų pajamingumo (Campbell ir Shiller, 1996). Rinkos lūkesčių privalumas yra jų orientacija į ateitį ir nuolatinis atnaujinimas, tačiau šie lūkesčiai gali būti iškraipyti rizikos premijų ar likvidumo pokyčių laikotarpiais ir neatspindėti namų ūkių bei įmonių perspektyvos (Christensen ir Gillan, 2012). **Įmonių infliacijos lūkesčiai.** Verslo infliacijos lūkesčiai atspindi įmonių prognozes, grindžiamas gamybos sąnaudomis, kainodaros sprendimais, darbo užmokesčio spaudimu ir bendromis ekonominėmis sąlygomis. Šie lūkesčiai taip pat pasižymi savaiminio išsipildymo principu, nes įmonės gali koreguoti kainas ar investicijas, remdamosi būsimos infliacijos anticipacija (Mankiw ir Reis, 2002). Verslo lūkesčiai dažniausiai nustatomi apklausų būdu, tačiau jų agregavimas gali paslėpti sektorių skirtumus ir sumažinti informacijos tikslumą (Carroll, 2003). **Vartotojų infliacijos lūkesčiai.** Vartotojų infliacijos lūkesčiai grindžiami namų ūkių kasdiene patirtimi, daro tiesioginę įtaką vartojimo bei darbo užmokesčio sprendimams ir yra nustatomi kiekybinėmis ir kokybinėmis apklausomis. Kiekybiniai klausimai leidžia gauti tikslius skaitinius įverčius, tačiau yra jautrūs ribotam finansiniam raštingumui, ryškiems kainų šokams ir ekstremaliems atsakymams (Bruine de Bruin ir kt., 2010; Armantier ir kt., 2016). Vartotojų apklausose naudojami kokybiniai klausimai sumažina kognityvinę našta respondentams, tačiau reikalauja papildomų kiekybinimo procedūrų, kurios gali įnešti paklaidų. Nepaisant didesnio nepastovumo ir šališkumo, vartotojų infliacijos lūkesčiai yra itin svarbūs dėl jų poveikio infliacijos dinamikai.

1.2.3. Ekonometrinis požiūris į lūkesčių matavimą

Ekonometrinis infliacijos lūkesčių vertinimas yra grindžiamas istorinių duomenų ir makroekonominių kintamųjų modeliavimu, taikant tiek paprastus laiko eilučių, tiek sudėtingesnius struktūrinius modelius. Šie metodai yra

sistemiški ir objektyvūs, tačiau dažniausiai orientuoti į praeitį ir neatspindi faktinių ekonominių agentų lūkesčių. Jų prognozinė galia priklauso nuo modelio specifikacijos, naudojamų prielaidų ir analizuojamo laikotarpio. Empiriniai tyrimai pateikia nevienareikšmius rezultatus, kai kuriais atvejais apklausomis pagrįsti lūkesčiai pagerina infliacijos prognozes (Faust ir Wright, 2013; Grothe ir Meyler, 2017), kitais – net paprasti ARMA modeliai juos pranoksta (Berge, 2018). Todėl pabrėžiama būtinybė vertinti prognozinį tikslumą skirtinguose laikotarpiuose (Stock ir Watson, 2010).

1.2.4. Diskusija dėl infliacijos lūkesčių poveikio

Empirinėje literatūroje nėra vieningos nuomonės dėl infliacijos lūkesčių poveikio faktinei infliacijai ir vartojimui. Rudd (2021) kvestionuoja į ateitį orientuotų lūkesčių svarbą, pabrėždamas uždelstos infliacijos ir pasiūlos veiksnių vaidmenį. Vėlesni tyrimai rodo, kad vartotojų infliacijos lūkesčiai yra labai heterogeniški ir dažnai silpnai prognozuoja faktinę infliaciją (Verbrugge ir Zaman, 2021; Weber, Coibion ir Gorodnichenko, 2023). Jų poveikis vartojimui priklauso nuo palūkanų normų lygio ir infliacijos režimo – esant aukštai infliacijai vyrauja tarplaikinio pakeitimo efektas, o žemos infliacijos laikotarpiais – pajamų efektas (Rondinelli ir Zizza, 2020). Taip pat, dėl ryškių skirtumų tarp šalių pabrėžiama nacionalinio konteksto svarba analizuojant infliacijos lūkesčių poveikį.

1.3. Naujausi infliacijos lūkesčių tyrimų rezultatai

Empiriniai tyrimai vis dažniau kvestionuoja racionalių ir gerai įtvirtintų infliacijos lūkesčių prielaidą, ypač padidėjusios infliacijos ir jos nepastovumo laikotarpiais. Naujausia literatūra išsiskiria metodologine įvairove ir didesniu dėmesiu lūkesčių formavimosi procesams, reakcijai į politiką bei elgsenos pasekmėms.

1.3.1. Matavimo inovacijos

Pastaruosiu metu infliacijos lūkesčių matavimas yra plečiamas naujomis apklausomis ir netiesioginiais metodais. ECB Vartotojų lūkesčių apklausa pagerina mikro-lygmens duomenų prieinamumą ir tarptautinį palyginamumą (Gomes ir kt., 2024; D'Acunto ir kt., 2024). Netiesioginiai klausimai apie reikiamų pajamų pokyčius leidžia tiksliau įvertinti namų ūkių lūkesčius, ypač riboto infliacijos supratimo atvejais (Hajdini ir kt., 2024). Aukšto dažnio duomenys leidžia taikyti įvykių analizę, o nauji įmonių apklausų moduliai

suteikia nuoseklius mikro-lygmens duomenis apie verslo infliacijos lūkesčius (Baumann ir kt., 2024).

1.3.2. Atsitiktinių imčių kontroliuojami eksperimentai

Atsitiktinių imčių eksperimentai (angl. *randomized controlled trials*, RCT) yra tapę svarbiu įrankiu analizuojant informacijos poveikį infliacijos lūkesčių formavimuisi ir jų pokyčiams. Tyrimai rodo, kad vartotojų žinios apie infliaciją ir pinigų politiką yra ribotos, remiantis Dräger ir Nghiem (2025), tik apie pusę Vokietijos vartotojų teisingai atsako į pagrindinius klausimus apie infliaciją, o ECB infliacijos tikslą žino tik nedidelė dalis respondentų. Tuo metu ne kiekybinė informacija apie infliaciją ir pinigų politiką, padidina infliacijos raštingumą, ypač – mažiau informuotų namų ūkių atžvilgiu, tačiau nei raštingumo didinimas, nei kiekybinės informacijos pateikimas reikšmingai nepagerina infliacijos lūkesčių tikslumo.

Kiti tyrimai rodo, kad informacijos poveikis priklauso nuo jos turinio ir pateikimo. Anot Dräger, Lamla ir Pfajfar (2024), informacija apie didėjančią infliaciją padidina tiek trumpalaikius, tiek ilgalaikius infliacijos lūkesčius, o profesionalių prognozių pateikimas šį poveikį sumažina. Vis dėlto, kai vėlesnė faktinė infliacija viršija pateiktas prognozes, informacijos poveikis silpnėja ir gali veikti net priešingai – respondentai grįžta prie ankstesnių įsitikinimų, įvyksta vadinamasis *informacijos apsvertimo* efektas. Remiantis Kostyshyna ir Petersen (2024) Kanados namų ūkių analize, informacija apie infliaciją ir jos prognozes reikšmingai sumažina tikėtiną infliaciją ir lūkesčių sklaidą. Stipriausias poveikis nustatomas pateikiant į ateitį orientuotą informaciją. Papildoma informacija apie infliacijos neapibrėžtumą pagerina lūkesčių įtvirtinimą, ypač tarp respondentų, kuriems būdingas didesnis subjektyvus neapibrėžtumas. Informacijos poveikis yra heterogeniškas – jaunesni ir mažiau išsilavinę asmenys reaguoja stipriau, o informacijos pateikimas taip pat padidina vartojimą artimiausiais mėnesiais. Panašūs tyrimo rezultatai gauti Jungtinėje Karalystėje po infliacijos piko (Fischer, Schnattinger ir Herler, 2025). Nustatyta, kad mažesnis infliacijos neapibrėžtumas didina planuojamą vartojimą ir keičia namų ūkių turto portfelio struktūrą. Kiti atsitiktinių imčių (RCT) tyrimai rodo, kad informacija apie valstybės skolą didina infliacijos ir nedarbo lūkesčius, tačiau centrinio banko patikimumas sušvelnina šį poveikį (Grigoli ir Sandri, 2024). Apibendrinant, RCT tyrimuose pabrėžiama tiek informacijos svarba valdant infliacijos lūkesčius, tiek ryškus namų ūkių reakcijų heterogeniškumas.

1.3.3. Lūkesčių heterogeniškumas ir formavimasis

Empiriniai tyrimai nuosekliai rodo, kad infliacijos lūkesčiai pasižymi dideliu heterogeniškumu ir sisteminiu šališkumu į viršų, lyginant su faktine infliacija. Analizuodami ECB Vartotojų lūkesčių apklausos duomenis, Gomes, Monteiro ir Ribeiro (2024) patvirtina reikšmingus skirtumus tarp namų ūkių infliacijos lūkesčius pagal amžių ir pajamas. Kliber ir kt. (2023) taip pat nustato, kad Centrinės ir Rytų Europos šalyse tiek vartotojai, tiek profesionalūs prognozuotojai dažnai netiksliai numato infliaciją, o valiutų kursų svyravimai yra svarbus prognozių paklaidų šaltinis. Naudodami netiesioginius infliacijos lūkesčių matavimus, Hajdini ir kt. (2024) pateikia išsamesnę heterogeniškumo apžvalgą – infliacijos lūkesčiai mažėja didėjant pajamoms, o jaunesniems respondentams dažniau būdingi žemesni infliacijos lūkesčiai. Tačiau, kai kuriose šalyse ryšys tarp amžiaus ir infliacijos lūkesčių nėra monotoniškas, o lyties skirtumai taip pat priklauso nuo šalies konteksto. Tai patvirtina, kad infliacijos lūkesčių formavimąsi stipriai veikia vietinė informacinė aplinka ir institucinės sąlygos. Be to, nustatyta, kad net labai lokaliuos patirtys, pavyzdžiui, miesto lygmens kainų pokyčiai, turi reikšmingą poveikį infliacijos lūkesčiams. Istorinių patirčių svarbą pabrėžia Braggion ir kt. (2025), nustatę ilgalaikius *atminties efektus* Vokietijos regionuose, labiau paveiktuose 1920-ųjų hiperinfliacijos. Kiti tyrimai analizuoja konkrečius lūkesčių formavimosi kanalus. Remiantis Dhamija, Nunes ir Tara (2025), formuodami infliacijos lūkesčius vartotojai pervertina būsto kainų augimo reikšmę, o heterogeniškumą ypač lemia kognityviniai gebėjimai ir neseni gyvenamosios vietos pokyčiai. Binder, Campbell ir Ryngaert (2024) nustato, kad namų ūkiai dažniausiai nereaguoja į pinigų politikos pranešimus, tačiau jautriai reaguoja į žiniasklaidos akcentuojamas naujienas. Stokman (2024) atkreipia dėmesį, kad energijos, maisto, transporto ir būsto kainos yra ypač svarbios euro zonos vartotojų lūkesčiams, o didesni infliacijos lūkesčiai dažniau siejami su didesniu vartojimu, esant žemoms palūkanų normoms. Empirinių tyrimų rezultatai dėl vartojimo reakcijos išlieka prieštaringi. Adams ir Barrett (2024) nustato defliacinę infliacijos lūkesčių šokų poveikį, o D'Acunto ir kt. (2024) pabrėžia, kad vartojimo reakcija į infliacijos lūkesčius yra labai heterogeniška ir stipriai priklauso nuo konteksto, išsilavinimo ir finansinio raštingumo.

1.3.4. Įmonių lūkesčiai

Naujausi tyrimai rodo, kad įmonių infliacijos lūkesčiai pasižymi daugeliu bruožų, būdingų namų ūkių lūkesčiams, nors tradiciškai buvo laikomi mažiau šališkais. Baumann ir kt. (2024), analizuodami euro zonos įmonių duomenis,

nustato didelį heterogeniškumą, kurį lemia įmonių ir jų vadovų charakteristikos bei veiklos aplinka. Įmonės dažnai ekstrapoluoja vietines ekonomines sąlygas į bendrą ekonomikos būklę, o tai lemia reikšmingą lūkesčių dispersiją. Atsitiktinių imčių eksperimentai su įmonėmis rodo, kad informacija apie ankstesnę infliaciją ir infliacijos prognozes reikšmingai keičia jų infliacijos lūkesčius, ypač pateikiant į ateitį orientuotą informaciją. Šie lūkesčių pokyčiai tiesiogiai veikia kainodaros, darbo užmokesčio, sąnaudų ir užimtumo planus, atskleiddami svarbų politikos komunikacijos kanalą. Remiantis Candia, Coibion ir Gorodnichenko (2024), JAV įmonių analize, įmonių vadovai dažnai yra menkai informuoti apie pinigų politiką ir infliaciją. Kaip ir namų ūkių atveju, infliacijos lūkesčiai pasižymi dideliu heterogeniškumu ir silpnu įtvirtinimu net ilgesniais laikotarpiais, dažnai nukrypstant nuo centrinio banko tikslo. Empiriniai tyrimai taip pat patvirtina priežastinį ryšį tarp įmonių lūkesčių ir jų investicinių bei užimtumo sprendimų, parodant, kad įmonių lūkesčiai yra svarbus makroekonominių procesų kanalas.

1.3.6. Baigiamosios pastabos

Mokslinės literatūros apžvalga patvirtina infliacijos lūkesčių svarbą šiuolaikinėje makroekonomikoje, tačiau kartu atskleidžia reikšmingas empirines ir metodologines spragas. Skirtingų ekonominių agentų infliacijos lūkesčiai dažnai yra netikslūs, heterogeniški ir kontekstiniai, o jų poveikis makroekonominiams rezultatams išlieka diskutuotinas. Šiomis išvalgomis grindžiama tolesnė empirinė analizė ir vartotojų infliacijos lūkesčių kiekybinimo metodų nagrinėjimas, kuris yra plėtojamas tolesniuose šio darbo skyriuose.

2. CARLSON–PARKIN KIEKYBINIMO METODAS: PRIELAIDOS IR PLĖTINIAI

2.1. Vartotojų apklausų duomenys

Europos Sąjungoje suderinta verslo ir vartotojų apklausų programa yra vykdoma nuo 1961 m. ir nuo to laiko yra nuolat atnaujinama bei tobulinama. Šią apklausą kas mėnesį atlieka Europos Komisija. Apklausos metu vartotojų prašoma įvertinti tiek kokybinį, tiek kiekybinį savo namų ūkio padėties ir bendros ekonominės situacijos suvokimą bei lūkesčius. Vienas pagrindinių klausimų, susijusių su infliacijos lūkesčiais, yra šeštasis klausimas: *Lyginant su dabartine padėtimi, kaip, Jūsų nuomone, per ateinančius 12 mėnesių keisis kainos: (a) didės sparčiau; (b) didės tokiu pačiu tempu; (c) didės lėčiau; (d)*

išliks maždaug tokios pačios; (e) šiek tiek sumažės? Panašus klausimas pateikiamas ir apie suvoktą infliaciją, t. y. kainų pokyčius, kuriuos vartotojai, jų nuomone, patyrė per pastaruosius 12 mėnesių (5 klausimas). Abu šie klausimai turi ir kiekybines alternatyvas (5.1 ir 6.1), tačiau mokslinėje literatūroje pabrėžiama, kad vartotojų pateikiami kiekybiniai infliacijos įverčiai sistemingai viršija oficialų HICP infliacijos rodiklį ir nėra patikimi lūkesčių matavimo instrumentai (Arioli ir kt., 2017; Rutkowska ir Szyszko, 2021). Dėl šios priežasties kokybiniai klausimai laikomi pranašesniais – jie pasižymi didesniu patikimumu, aukštesniu atsakymų dažniu ir mažesne kognityvine našta respondentams. Be to, kokybiniai infliacijos lūkesčių klausimai leidžia surinkti išsamesnius duomenis (Pesaran ir Weale, 2005). Tačiau, tokie atsakymai tiesiogiai neatskleidžia lūkesčių dydžio, todėl kyla poreikis kokybinius atsakymus paversti kiekybiniais rodikliais. Paprasčiausias ir ankstyviausias bandymas kiekybinti kokybinius atsakymus yra balanso statistika (Anderson Jr., 1952), kuri pateikiama kartu su apklausų rezultatais. Balanso statistika apskaičiuojama kaip skirtumas tarp vartotojų, tikinčių kainų augimu, ir vartotojų, tikinčių kainų kritimu, dalies. Penkių kategorijų klausimyne balanso statistika apskaičiuojama taip:

$$BS_t = A_t \times 1 + B_t \times 0.5 + C_t \times 0 + D_t \times (-0.5) + E_t \times (-1) \quad (1)$$

Kur A_t, B_t, C_t, D_t, E_t žymi respondentų proporcijas, pasirinkusias atitinkamus atsakymus laiko momentu t . Nors balanso statistika yra paprasta ir plačiai naudojama, tačiau jos skaičiavimas sulieja kryptį ir dydį. Sviurių vertės taip pat yra kvestionuotinos. Dėl šių apribojimų, tyrimuose plėtojami sudėtingesni kiekybinimo metodai. Tarp jų svarbiausi yra tikimybinis metodas, plačiai žinomas kaip Carlson–Parkin metodas, ir regresinis metodas, išpopuliarintas Pesaran.

2.2. Carlson–Parkin metodas

Carlson–Parkin metodas kyla iš tikimybės prieigos, kuriame kokybiniai apklausų atsakymai interpretuojami kaip implicitiniai subjektyvių tikimybių skirstinių signalai (Thiel, 1952; Carlson ir Parkin, 1975). Šis metodas remiasi prielaidomis apie vienodą ir simetrišką respondentų nepastabumo intervalą bei pasirinktą skirstinio formą, kuri lemia perėjimą nuo kokybinių kategorijų prie kiekybinių infliacijos lūkesčių. Batchelor ir Orr (1988) išplėtė šį metodą penkių kategorijų duomenims, taip sudarydami sąlygas jį taikyti Europos Komisijos vartotojų apklausoms. Skirstinio pasirinkimas yra esminė šio metodo prielaida. Nors normalusis skirstinys ilgą laiką buvo naudojamas kaip

standartas, empiriniai tyrimai rodo, kad infliacijos lūkesčiai dažnai yra asimetriški ir labiau paveikti stebimų kainų pokyčių (Batchelor, 1981). Nepaisant to, vėlesniuose tyrimuose nustatyta, kad alternatyvūs skirstiniai dažnai suteikia tik ribotą prognozinio tikslumo pagerėjimą, todėl normalumo prielaida tapo pragmatišku pasirinkimu. Dauguma naujesnių tyrimų naudoja Carlson–Parkin metodą kanonine forma ir koncentruojasi į lūkesčių prognozinį tikslumą, makroekonominę efektyvumą ir heterogeniškumą tarp šalių (Rutkowska ir Szyszko, 2019; Kliber ir kt., 2023) ir tik keli darbai tiesiogiai nagrinėja metodo prielaidas. Lolić ir Sorić (2017) tyrimas rodo ribotą skirstinio pasirinkimo naudą agreguotuose duomenyse, o Rutkowska, Szyszko ir Pietrzak (2023) atskleidžia, kad optimalios prielaidos priklauso nuo vertinimo kriterijaus ir šalies. Vis dėlto, klausimai dėl sub-optimalaus skirstinio pasirinkimo kaštų ir euro įvedimo poveikio lūkesčių formavimuisi lieka neatsakyti, ypač Baltijos šalyse, kur infliacija ir infliacijos lūkesčiai pasižymi dideliu nepastovumu.

Lentelė 1. Tyrimai testuojantys ne normalius skirstinius CP metodo taikyme.

Autorius. Tyrimo pavadinimas	Tiriama šalis	Rezultatai
Batchelor ir Orr (1988). <i>Inflation Expectations Revisited</i>	JK	Logistinio skirstinio prielaida grindžiamas metodas yra patobulinimas, palyginti su normaliuoju skirstiniu (RMSE santykis – 1.129).
Berk (1999). <i>Measuring Inflation Expectations: a Survey Data Approach</i>	Nyderlandai	Leidimas skirstiniui pasižymėti nenormaliu smailumu (centrinis t skirstinys) ir asimetrija (necentrinis t skirstinys) nepadidino vartotojų infliacijos prognozių tikslumo (RMSE santykiai – 0.702–1.031).
Nielsen (2003). <i>Inflation Expectations in the EU - Results from Survey Data</i>	EU šalių agreguoti duomenys (Belgija, Nyderlandai, Liuksemburgas, Prancūzija, Vokietija, Italija, Airija, JK, Danija ir Graikija, nuo 1986 Portugalija and Ispanija, bei nuo 1995 Suomija, Švedija ir Austrija)	Tiek leptokurtiniai, tiek asimetriški skirstiniai nepagerina infliacijos prognozavimo kokybės.
Lyziak (2003). <i>Consumer Inflation Expectations in Poland</i>	Lenkija	Tolygiojo skirstinio taikymas lėmė mažesnę vartotojų lūkesčių tikslumą, palyginti su normaliuoju skirstiniu (analizuotų laikotarpių RMSE santykis svyruoja nuo 0.786 iki 0.913).
Lolic ir Soric (2017). <i>A critical re-examination of the Carlson - Parkin method</i>	Agreguoti euro zonos duomenys	Buvo išbandyti keli skirtingi modeliai ir skirstiniai. Tyrimas parodė, kad daugumoje modelių geriausi rezultatai gaunami naudojant centrinį t skirstinį. Tačiau tyrėjai padarė išvadą, jog normalaus skirstinio alternatyvos užtikrina tik nežymius infliacijos lūkesčių tikslumo pagerinimus (RMSE santykiai iki 1.056).

Rutkowska, Szyszko ir Pietrzak (2023). <i>When all we have is not enough: a search for the optimal method of quantifying inflation expectations</i>	Austrija, Belgija, Vokietija, Ispanija, Suomija, Prancūzija, Graikija, Italija, Nyderlandai, Portugalija, Bulgarija, Kroatija, Čekija, Danija, Vengrija, Lenkija, Rumunija, Švedija ir JK	Buvo testuojami normalusis, tolygusis, logistinis, Stjudento t ir asimetriškas Stjudento t skirstiniai. Nustatyta, kad atskiroms šalims optimalios yra skirtingos procedūros. Straipsnyje nepateikiama informacija apie prognozių tikslumą.
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2.3. Kokybinių lūkesčių kiekybinimas

Carlson–Parkin metodo taikymas remiasi prielaida, kad vartotojų infliacijos lūkesčiai kyla iš individualių subjektyvių tikimybių skirstinių, kurie gali būti agreguojami į bendrą skirstinį, o lūkesčių formavimąsi apibrėžia du nepastabumo intervalai (Nielsen, 2003). Praktikoje šis metodas yra dažnai papildomas supaprastinančiomis prielaidomis apie ilgalaikį nešališkumą, simetriškus neįtakojimo intervalus ir normalųjį agreguotą skirstinį, nors šios prielaidos nėra būtinos pačiam kiekybinimo procesui.

Tyrimai rodo, kad šios prielaidos dažnai yra pernelyg ribojančios, ypač ekonominėse aplinkose, pasižyminčiose dideliu infliacijos nepastovumu ar ribotu finansiniu raštingumu. Normaliojo skirstinio atveju, kokybiniai atsakymai susiejami su skirstinio intervalais, leidžiančiais iš respondentų proporcijų ir mastelio parametro išvesti tikėtiną infliaciją, dispersiją bei nepastabumo ribas. Taigi kiekybiniai infliacijos lūkesčiai yra jautrūs tiek pasirinktai skirstinio formai, tiek mastelio parametro apibrėžimui.

3. VARTOTOJŲ INFLIACIJOS LŪKESČIŲ KIEKYBINIMAS IR TIKSLUMAS BALTIJOS ŠALYSE

Šiame skyriuje dėmesys sutelkiamas į Carlson–Parkin (CP) metodo skirstinio prielaidą, kiekybinant vartotojų infliacijos lūkesčius Baltijos šalyse. Ankstyvoji literatūra apie CP metodą daugiausia nagrinėjo jo prielaidas, tačiau dauguma naujesnių tyrimų taiko standartinę šio metodo formą ir analizuoja įvairius vartotojų infliacijos lūkesčių aspektus, tokius kaip jų tikslumas, formavimosi veiksniai, racionalumas ir prognozinis pobūdis (Kliber, Szyszko, Prochniak ir Rutkowska, 2023; Rutkowska ir Szyszko, 2022; Szyszko, Rutkowska ir Kliber, 2020 ir kt.).

Naujesni darbai, tiesiogiai nagrinėjantys patį CP metodą (Lolić ir Sorić, 2017; Szyszko, Rutkowska ir Pietrzak, 2023), paliko keletą svarbių neatsakytų klausimų. Lolić ir Sorić (2017) analizuoja infliacijos lūkesčių tikslumą taikant ne normalųjį skirstinį, tačiau jų analizė apsiriboja agreguotais euro zonos duomenimis ir neatsižvelgia į atskirų šalių infliacijos dinamikos bei vartotojų atsakymų heterogeniškumą. Szyszko, Rutkowska ir

Pietrzak (2023) pripažįsta lūkesčių heterogeniškumą, tačiau nepateikia kiekybinio įvertinimo, kokius kaštus turi neoptimalus skirstinio pasirinkimas. Be to, į šį tyrimą neįtrauktos Baltijos šalys, nes analizuojamu laikotarpiu jos įsivedė eurą.

Atsižvelgiant į minėtą problematiką, šiame skyriuje keliami trys pagrindiniai tikslai. Pirma, siekiama įvertinti, kokią kiekybinę naudą suteikia optimalaus tikimybinio skirstinio pasirinkimas ir palyginti tai su standartinė normalumo prielaida. Antra, siekiama užpildyti mokslinio diskurso spragą, susijusią su vartotojų infliacijos lūkesčių kiekybinimu Baltijos šalyse ir įvertinti, ar euro įvedimas turėjo reikšmingą poveikį lūkesčių kiekybinimo rezultatams. Nors pagrindinis dėmesys skiriamas Baltijos šalims, papildomai analizuojami Lenkijos ir agreguoti euro zonos duomenys, taip siekiant išlaikyti palyginamumą su ankstesniais tyrimais. Trečia, tikrinamas Baltijos šalių vartotojų infliacijos lūkesčių prognozinių pobūdis ir jų gebėjimas numatyti būsimą infliaciją.

3.2. Infliacijos lūkesčių kiekybinimas

Vartotojų infliacijos lūkesčiai kiekybinami taikant Carlson–Parkin metodą su penkiais skirtingais skirstiniais: normaliuoju, logistiniu, centruotu t ir dviem necentruotais t skirstiniais. Necentruotų t skirstinių taikymas reikalauja papildomo necentriškumo parametro. Šiame tyrime daroma prielaida, kad balanso statistika seka autoregresinį arba atsitiktinio klaidžiojimo procesą, todėl necentriškumo parametras aproksimuojamas nesąlygine matematine viltimi arba imties vidurkiu. Vienetinės šaknies testai patvirtina, kad daugeliu atvejų balanso statistika elgiasi kaip atsitiktinio klaidžiojimo procesas.

Papildomai taikomas Berk (1999) pasiūlytas necentriškumo parametras, leidžiantis fiksuoti trumpalaikius infliacijos nukrypimus nuo vidutinių laikotarpio tendencijų. Kiekybinimui naudojami keturi mastelio parametrai: faktinė ir uždelsta faktinė infliacija bei du suvoktos infliacijos rodikliai, gauti iš kokybinių vartotojų atsakymų. Suvokta infliacija apibrėžiama remiantis faktine infliacija prieš 12 mėnesių arba *vidutinės infliacijos* samprata, grindžiama viso laikotarpio vidurkiu.

Kiekybinių lūkesčių tikslumas vertinamas naudojant RMSE, lyginant lūkesčius su faktine metine infliacija po 12 mėnesių. Nors ši metrika yra standartinė, ji interpretuojama kaip empirinio prognozavimo tikslumo rodiklis, o ne kaip lūkesčių racionalumo kriterijus (Rutkowska ir kt., 2022).

RMSE rezultatai rodo, kad vartotojų infliacijos lūkesčiai Baltijos šalyse yra sistemingai mažiau tikslūs nei Lenkijoje ir euro zonoje beveik visose nagrinėtose imtyse. Daugumoje laikotarpių RMSE reikšmės Baltijos šalyse

yra pastebimai didesnės, o tai reiškia didesnę nuokrypį tarp kiekybiškai įvertintų lūkesčių ir faktinės infliacijos po 12 mėnesių. Šis skirtumas sumažėja 2012–2020 m. laikotarpiu, kai infliacijos dispersija Lenkijoje tampa artimesnė Baltijos šalims ir RMSE reikšmės tarp šių šalių suartėja, patvirtindamos ryšį tarp infliacijos nepastovumo ir lūkesčių tikslumo. Alternatyvių skirstinių taikymas, palyginti su normaliojo skirstinio prielaida, daugumoje atvejų lemia tik nedidelius tikslumo pokyčius. RMSE santykiei dažniausiai artimi 1, o tikslumo pagerėjimai dažniausiai neviršija kelių procentų. Vis dėlto, išsiskiria konkretūs laikotarpiai ir šalys. Naudojant necentrinį t skirstinį, kurio necentriškumo parametras grindžiamas balanso statistikos vidurkiu, Lietuvoje 2001–2019 m. laikotarpiu RMSE sumažėja apie 6,4 %, o 2012–2020 m. laikotarpiu ir iki euro įvedimo – itin reikšmingai. Iki euro įvedimo Lietuvoje RMSE sumažėja net apie 62,3 %, o kai kuriose specifinėse konfigūracijose – iki 72,3 %, rodant, kad normaliojo skirstinio prielaida tuo laikotarpiu buvo ypač netinkama. Tokie tikslumo pagerėjimai nėra stebimi Lietuvoje po euro įvedimo ir taip pat nėra fiksuojami Latvijoje ar Estijoje analogiškais laikotarpiais. Latvijos atveju tai siejama su tuo, kad po euro įvedimo sumažėjo ne tik vartotojų lūkesčiai, bet ir faktinė infliacija, o Lietuvoje vartotojų lūkesčių kritimas nebuvo lydimas atitinkamo infliacijos sumažėjimo. Naujausiame laikotarpyje (2020–2023 m.) necentrinio t skirstinio taikymas Baltijos šalyse lemia nežymiai didesnes RMSE reikšmes, o Lenkijoje – aiškų tikslumo pablogėjimą, palyginti su normaliuoju skirstiniu.

Rezultatai rodo, kad mastelio parametro pasirinkimas daro įtaką absoliučioms RMSE reikšmėms, tačiau beveik nekeičia skirstinių tarpusavio santykių. Visos imties atveju tiksliausi rezultatai dažniausiai gaunami naudojant uždelstą faktinę infliaciją (π_{t-1}), tačiau skirtumai tarp π_t ir π_{t-1} yra nereikšmingi. Kai CP metodas taikomas ir suvoktai infliacijai, absoliučios RMSE reikšmės padidėja, tačiau santykiniai skirstinių rezultatai išlieka panašūs. Išimtis pastebima tik Estijoje 2012–2020 m. laikotarpiu, kai tikslumo pagerėjimai padidėja iki maždaug 14,2 %. Apskritai rezultatai rodo, kad nors skirstinio pasirinkimas gali turėti reikšmingą poveikį specifiniuose laikotarpiuose, normaliojo skirstinio taikymas dauguma atvejų lemia tik nedidelius tikslumo nuostolius. Reikšmingi tikslumo pagerėjimai koncentruojasi konkrečiuose laikotarpiuose, ypač Lietuvoje iki euro įvedimo, ir nėra universalūs visoms šalims ar laikotarpiais. Lenkijoje normalusis skirstinys išlieka nuosekliausiai tikslus, o euro zonos atveju centrinis t skirstinys suteikia nedidelius, iki maždaug 2,2 % siekiančius, tikslumo pagerėjimus, tai atitinka Lolić ir Sorić (2017) tyrimo išvadas. Tai rodo, kad optimalus skirstinio pasirinkimas yra kontekstinis ir ypač jautrus struktūriniam lūžiams, tokiems kaip valiutos pakeitimas.

3.3. Kiekybiškai įvertintų vartotojų infliacijos lūkesčių prognozinė galia

Tyrimų rezultatai rodo, kad daugumoje šalių kiekybiškai įvertinti vartotojų infliacijos lūkesčiai turi labai ribotą prognozinę galią. Visoje imtyje Lietuvoje lūkesčių koeficientas nėra statistiškai reikšmingas, o jų įtraukimas į regresiją beveik nekeičia $R^2(\text{adj},c)$. Latvijoje fiksuojamas didžiausias $\Delta R^2(\text{adj},c)$, tačiau Estijoje $R^2(\text{adj},c)$ įgauna neigiamas reikšmes, rodydamas, kad paprastas infliacijos vidurkis prognozuoja geriau, nei modelis su lūkesčiais. Daugelyje laikotarpių balanso statistikos suteikia didesnę $\Delta R^2(\text{adj},c)$ nei kiekybiniai lūkesčiai, nors išimtis yra Lenkija, kur abiejų rodiklių prognozinė galia yra panaši. 2001–2019 m. imtyje euro zonos atveju $R^2(\text{adj},c)$ pagerėja labiau nei pilnoje imtyje, o Latvijos ir Estijos duomenims $\Delta R^2(\text{adj},c)$ padidėja, tačiau išlieka ribotas. Kitose imtyse $\Delta R^2(\text{adj},c)$ dažniausiai yra nedidelis dėl kolinearumo ir mažesnių imčių.

Išskirtinis atvejis yra 2020–2023 m. laikotarpis euro zonoje, kai lūkesčių įtraukimas reikšmingai pagerina modelio pritaikymą, patvirtindamas, kad aukštos infliacijos sąlygomis lūkesčių prognozinė vertė didėja (Mitchell ir Zaman, 2023). Toks efektas nėra stebimas Baltijos šalyse. Lenkijoje geresnis regresijos pritaikymas daugiausia kyla iš stipresnio bazinio modelio, o ne iš vartotojų lūkesčių indėlio. Apskritai rezultatai patvirtina, kad individualių šalių lygmeniu kiekybiškai įvertinti vartotojų lūkesčiai retai suteikia stabilios ir reikšmingos papildomos prognozinės informacijos, priešingai nei nustatyta JAV atveju (Verbrugge ir Zaman, 2021).

3.4. Baigiamosios pastabos

Šiame tyrime kokybiniai vartotojų infliacijos lūkesčiai įvertinami kiekybiškai, taikant Carlson–Parkin metodą ir naudojant skirtingas prielaidas dėl vartotojų atsakymų skirstinio bei mastelio parametro Lietuvai, Latvijai, Estijai, Lenkijai ir euro zonai. RMSE rezultatai rodo, kad necentrinis t skirstinys, kurio necentriškumo parametras grindžiamas vartotojų atsakymų balanso statistikos vidurkiu, kai kuriais atvejais leidžia pasiekti nedidelius tikslumo pagerėjimus Baltijos šalyse, lyginant su normaliojo skirstinio prielaida. Lenkijos atveju, normalusis skirstinys daugumoje konfigūracijų suteikia tiksliausius rezultatus, o euro zonos agreguoti vartotojų lūkesčiai yra tiksliausi taikant centrinį t skirstinį ir atitinka ankstesnių empirinių tyrimų rezultatus. Tačiau tiek Lenkijos, tiek euro zonos atveju tikslumo pagerėjimai yra nereikšmingi, todėl netinkamo skirstinio pasirinkimo kaina dažniausiai yra labai maža. Vieninteliai reikšmingi tikslumo pagerėjimai naudojant necentrinį t skirstinį nustatyti Lietuvoje iki euro įvedimo. Nors faktinės infliacijos

dinamika prieš ir po euro įvedimo kito nedaug, tačiau vartotojų atsakymų dinamika po euro įvedimo reikšmingai pasikeitė – necentrinio t skirstinio taikymas leido gauti gerokai tikslesnius rezultatus. Tai ypač aktualu laikotarpiais, kai vartotojų lūkesčiai dėl būsimų kainų raidos yra nepagrįstai aukšti, kaip buvo stebėta Lietuvoje iki euro įvedimo.

RMSE analizė taip pat rodo, kad mastelio parametro pasirinkimas turi didesnę poveikį kiekybiškai įvertintų vartotojų lūkesčių tikslumui, nei skirstinio pasirinkimas, tačiau toks tikslumo vertinimas remiasi prielaida apie vartotojų lūkesčių nešališkumą. Atsižvelgiant į tai, kad vartotojų lūkesčiai gali būti sistemingai šališki, modelių parinkimas remiantis vien RMSE kriterijumi nebūtinai atspindi tikrąją vartotojų nuostatą. Vis dėlto, t mažiausios RMSE reikšmės gali būti naudingos renkantis geriausias prognozavimo savybes turintį modelį.

Tuo metu mastelio parametro pasirinkimas beveik neturėjo įtakos optimalaus skirstinio pasirinkimui. Vertinant skirstinių tikslumą pagal RMSE santykius, mastelio parametro pasirinkimas jų reikšmingai nekeičia, o tai praktiniu požiūriu yra reikšminga politikos formuotojams ir ekonomistams, siekiantiems tobulinti infliacijos prognozavimo priemones.

Vartotojų atsakymų analizė rodo, kad vartotojai iš esmės yra orientuoti į ateitį, tačiau jų svarstomas laiko horizontas dažniausiai yra trumpesnis nei 12 mėnesių. Kryžminės koreliacijos rodo, kad didžiausios reikšmės pasiekiamos esant 6–8 mėnesių horizontui atskirose šalyse ir apie 4 mėnesių horizontui euro zonos agreguotuose duomenyse visos imties atveju. Tačiau trumpesnių imčių rezultatai nėra vienareikšmiai. 2012–2020 m. laikotarpiu Baltijos šalių vartotojai atrodo labiau orientuoti į praeitį, tuo tarpu Lenkijos ir euro zonos duomenys rodo didžiausią ryšį su einamojo periodo infliacija. Panašios išvados gaunamos ir analizuojant kiekybiškai įvertintų vartotojų lūkesčių prognozinę galią.

Prognozinės galios analizė rodo, kad Lietuvos atveju kiekybiškai įvertinti vartotojų lūkesčiai nėra orientuoti į ateitį ir nėra tikslūs prognozuojant metinę infliaciją po 12 mėnesių visos imties atveju. Trumpesnių imčių analizė patvirtina, kad daugumoje konfigūracijų vartotojų lūkesčiai reikšmingai nepagerina bazinio modelio nei atskirose šalyse, nei euro zonoje. Vieninteliai laikotarpiai, kai kiekybiškai įvertinti vartotojų lūkesčiai reikšmingai pagerina bazinį modelį, yra pastarasis aukštos infliacijos laikotarpis euro zonoje bei laikotarpis po euro įvedimo Lietuvoje ir Latvijoje. Siekiant geriau paaiškinti šiuos rezultatus, tikslinga atlikti tolesnius vartotojų laiko horizonto suvokimo, lūkesčių formavimosi ir informacijos vartojimo įpročių empirinius tyrimus.

4. CARLSON–PARKIN SPECIFIKACIJŲ LYGINAMASIS VERTINIMAS NAUDOJANT PVAR MODELĮ

Infliacijos lūkesčių vaidmuo makroekonomikoje tapo ypač aktualus po 2021 m. infliacijos šuolio, tačiau empirinių įrodymų apie vartotojų lūkesčių poveikio ekonomikai stiprumą ir patvarumą vis dar trūksta. Šiame skyriuje vartotojų infliacijos lūkesčiai analizuojami panelinio VAR modelio kontekste, siekiant įvertinti jų dinaminę sąveiką su pagrindiniais makroekonominiais rodikliais ES šalyse. Analizė grindžiama keliomis Carlson–Parkin metodo specififikacijomis ir balanso statistika, leidžiančiomis įvertinti, kaip ir kiek reikšmingai lūkesčių kiekybinimo būdas lemia empirines išvadas. Rezultatai rodo, kad makroekonominių ryšių stiprumas ir kryptis gali būti jautrūs pasirinktai lūkesčių matavimo metodikai, o tai pabrėžia metodologinių sprendimų svarbą vertinant vartotojų nuotaikų kanalą. Taip pat nustatomas ryškus infliacijos lūkesčių poveikio heterogeniškumas tarp ES šalių. Tai reiškia, kad agreguotos euro zonos ar ES analizės gali maskuoti reikšmingus nacionalinius skirtumus, todėl individualių šalių duomenų analizė suteikia papildomos informacijos apie vartotojų lūkesčių vaidmenį makroekonominiuose procesuose. Šie rezultatai pagrindžia poreikį derinti metodologiškai nuoseklų lūkesčių kiekybinimą su tarp-šalinių heterogeniškumu, ypač formuojant pinigų politikos vertinimus ir rekomendacijas.

4.1. Metodas

Dinaminėms sąsajoms tarp infliacijos lūkesčių ir pagrindinių makroekonominių kintamųjų ES šalyse vertinti taikomas panelinis VAR modelis, leidžiantis modeliuoti tarpusavyje priklausomų kintamųjų dinamiką. Analizė grindžiama ketvirtiniais duomenimis dvidešimt šešioms šalims 2004K1–2024K3 laikotarpiu, su vidutiniškai apie 65 stebėjimais vienai šaliai, todėl Nickell šališkumo rizika laikoma ribota, bet papildomai tikrinama. Modelis vertinamas tiek OLS su fiksuotaisiais efektais, tiek sisteminio GMM metodu, leidžiančiu įvertinti galimą endogeniškumą. GMM taikymas yra vertinamas kritiškai dėl instrumentų pertekliaus rizikos ir didesnių standartinių paklaidų, o instrumentų tinkamumas tikrinamas Hansen J testu. Tai leidžia įvertinti variacijos ir šališkumo kompromisą tarp skirtingų vertinimo metodų.

Visi endogeniniai kintamieji apibrėžiami metiniais pokyčiais (YoY), taip užtikrinant stacionarumą ir sumažinant reikiamų vėlavimų skaičių. Naudojamas modelis apima vartojimą, BVP, valdžios išlaidas, kreditą,

infliaciją, nedarbą, palūkanų normas, indėlius, darbo užmokestį, energijos kainas ir vartotojų pasitikėjimo rodiklį. Tai atitinkamai leidžia įvertinti pagrindinius kanalus, per kuriuos infliacijos lūkesčiai gali veikti ekonomiką. Infliacijos lūkesčiai matuojami dviem alternatyviais būdais: naudojant balanso statistikos pokyčius ir kiekybiškai įvertintus vartotojų lūkesčius pagal Carlson–Parkin metodą. Vieno uždelsimo PVAR specifikacija leidžia įvertinti trumpalaikes dinamines sąsajas tarp lūkesčių ir kitų makroekonominių kintamųjų, kartu išlaikant modelio skaičiavimo stabilumą ir interpretacinį aiškumą.

4.2. Rezultatai

OLS ir GMM PVAR modelių palyginimas rodo sistemingus skirtumus koeficientų dydžiuose ir patvarume. OLS modelyje koeficientai dažnai yra kelis kartus didesni nei GMM. Pavyzdžiui, uždelsto realaus BVP augimo poveikis infliacijos lūkesčiams siekia 0.51 ($p < 0.001$) OLS modelyje, bet sumažėja iki 0.05 ($p < 0.05$) GMM modelyje. Valdžios išlaidų augimo poveikis infliacijos lūkesčiams OLS modelyje yra 0.14 ($p < 0.01$), o GMM modelyje tampa statistiškai nereikšmingas ($-0,02$). Hansen J testas ($p > 0,1$) neleidžia atmesti instrumentų tinkamumo, tačiau GMM impulsų atsako funkcijų 95 % pasikliautiniai intervalai dažnai apima nulį ir tai rodo didelį neapibrėžtumą.

Vieno standartinio nuokrypio realaus vartojimo augimo šokas OLS modelyje padidina vartojimą apie 3.7 proc. punkto pirmą ketvirtį, o poveikis išlieka teigiamas apie 6 ketvirčius. Realus BVP augimas padidėja apie 2.2 proc. punkto, o poveikis išnyksta po 4–5 ketvirčių. Nedarbo lygis sumažėja apie 0.22 proc. punkto, grįždamas į pradinį lygį per 5–6 ketvirčius. Infliacija reaguoja kupolo forma, pasiekdama piką apie 0.56 proc. punkto po 4 ketvirčių, o energijos kainos padidėja iki 2.4 proc. punkto po 2–3 ketvirčių. Infliacijos lūkesčiai padidėja apie 1.4 balanso statistikos vieneto iš karto ir pasiekia piką (~ 2.3 vieneto) po 1 ketvirčio, tačiau po 5–6 ketvirčių tampa neigiami. GMM modelyje pradiniai poveikiai yra didesni (vartojimui ~ 4.4 proc. punkto), bet išnyksta per 2–3 ketvirčius ir dažnai nėra statistiškai reikšmingi. Valdžios išlaidų šokas OLS modelyje padidina realų vartojimą apie 0.37 proc. punkto, su piku apie 0.5 proc. punkto po 2–3 ketvirčių, o pats valdžios išlaidų augimas išlieka padidėjęs apie 8 ketvirčius (pradinis poveikis ~ 3.9 proc. punkto). Darbo užmokestis padidėja apie 0.7 proc. punkto, o kiti kintamieji reaguoja silpnai. GMM modelyje reikšmingas poveikis nustatomas praktiškai tik darbo užmokesčiui. Infliacijos šokas yra itin patvarus – poveikis išlieka ilgiau nei 8 ketvirčius. Darbo užmokestis reaguoja tik po 3–4 ketvirčių, ir labai silpnai

(~0.25 proc. punkto), tai rodo atlyginimų–kainų spiralės nebuvimą. Namų ūkių indėliai sumažėja su vėlavimu, pasiekdami apie -0.67 proc. punkto po 8 ketvirčių. Infliacijos lūkesčiai iš karto padidėja apie 3.4 balanso vieneto, bet po 3 ketvirčių grįžta į pradinį lygį ir ilgainiui tampa neigiami (~-2 vienetai). Vartotojų pasitikėjimas sumažėja apie -1.1 vieneto, tačiau atsistato per 6 ketvirčius. Nedarbo šokas sukelia stiprų neigiamą poveikį vartojimui (-1.3 proc. punkto) ir BVP (-1.1 proc. punkto), o poveikis išnyksta per 5–6 ketvirčius. Infliacijos reakcija yra labai silpna (~0.1–0.16 proc. punkto) ir vos reikšminga ir tai prieštarauja standartinei Phillips kreivės interpretacijai. Infliacijos lūkesčiai ir vartotojų pasitikėjimas sumažėja apie -1 balanso vieneta, bet atsistato per 3 ketvirčius. Infliacijos lūkesčių šokas trumpuoju laikotarpiu padidina vartojimą apie 0.4 proc. punkto, tačiau po 3–4 ketvirčių poveikis išnyksta, o vėliau tampa neigiamas. Infliacija reaguoja iš karto (~1.1 proc. punkto) ir poveikis išlieka ilgiau nei 8 ketvirčius. Darbo užmokestis nereaguoja, o vartotojų pasitikėjimas sumažėja ir išlieka žemesnis apie du metus. Vartotojų pasitikėjimo šokas skatina vartojimą ir BVP, bet infliacijos lūkesčių reakcija yra netiesioginė: pradinis sumažėjimas (-3.9 vieneto), vėliau – teigiamas efektas, pasiekiantis apie 2.6 vieneto po 4 ketvirčių. Rezultatai rodo, kad paklausos šokai sukelia kiekybiškai reikšmingas, bet laikinas reakcijas, infliacijos ir infliacijos lūkesčių poveikiai yra patvarūs, o atlyginimų–kainų spiralė analizuotu laikotarpiu nepasireiškia. Infliacijos lūkesčiai veikia ekonomiką asimetriškai: trumpuoju laikotarpiu skatindami vartojimą, bet vidutiniu laikotarpiu sukeldami neigiamą grįžtamąjį ryšį.

4.3. Carlson–Parkin metodas ir panelinis VAR

Infliacijos lūkesčiai į PVAR sistemą įtraukiami trimis Carlson–Parkin (CP) metodu sukiekybintais variantais, visais atvejais darant normaliojo skirstinio prielaidą, bet naudojant skirtingus mastelio parametrus: (1) faktinę metinę infliaciją (PI_EXP1), (2) dviejų metų slenkantį infliacijos vidurkį (PI_EXP2), (3) CP metodu įvertintą suvoktą infliaciją, skalę apibrėžiant dviejų metų infliacijos vidurkiu (PI_EXP3).

Visais atvejais impulsų atsako funkcijos rodo, kad bendroji makroekonominė dinamika išlieka panaši, palyginti su modeliu, kuriame naudojami balanso statistikos pokyčiai (BS_YOY). Skirtumai daugiausia pasireiškia lūkesčių, pasitikėjimo ir finansinių kintamųjų kanaluose, o ne pagrindiniuose paklausos ar kainų lygio atsakuose. Lyginant BS_YOY ir PI_EXP1_YOY modelius, daugumos kintamųjų reakcijų kryptis ir trukmė sutampa. Tačiau, pastebimi keli kiekybiškai reikšmingi skirtumai. Vartotojų pasitikėjimo indeksas po nedarbo šoko abiejuose modeliuose iš pradžių

mažėja panašiu mastu, tačiau PI_EXP1 specifikacijoje po maždaug 5 ketvirčių atsiranda teigiamas ilgalaikis poveikis, siekiantis apie 0.3–0.4 indekso vieneto, kuris BS modelyje nėra statistiškai reikšmingas. Namų ūkių indėlių reakcija į infliacijos lūkesčių šoką taip pat skiriasi: BS modelyje poveikis yra nereikšmingas, o PI_EXP1 modelyje po 4 ketvirčių fiksuojamas -0.6 iki -0.7 proc. punkto kritimas, rodantis stipresnį taupymo-kainų kanalo aktyvumą. Naudojant PI_EXP2_YOY, bendros reakcijų kryptys išlieka tos pačios, tačiau padidėja poveikių patvarumas. Energijos kainų reakcijos į infliacijos ir infliacijos lūkesčių šokus išlieka reikšmingos ilgiau nei 6–8 ketvirčius, lyginant su trumpesne dinamika BS ir PI_EXP1 modeliuose. Vartotojų pasitikėjimo reakcijos tampa didesnės amplitudės ir lėčiau grįžta į pradinį lygį, o tai rodo stipresnį lūkesčių-sentimento grįžtamąjį ryšį, kai lūkesčiai formuojami labiau inertiškai. Modelyje su PI_EXP3_YOY išryškėja ryškiausi skirtumai sentimentų kanale. Infliacijos lūkesčių šokas nebesukelia statistiškai reikšmingos vartotojų pasitikėjimo reakcijos, priešingai nei ankstesniuose modeliuose. Tuo metu teigiamas vartotojų pasitikėjimo šokas sukelia teigiamą ir patvarų infliacijos lūkesčių atsaką, kuris ankstesnėse specifikacijose buvo neigiamas arba trumpalaikis. Šis efektas rodo ženklų krypties pasikeitimą. Be to, PI_EXP3 specifikacijoje faktinė infliacija reaguoja į infliacijos lūkesčių šoką maždaug perpus silpniau nei BS ar PI_EXP1 modeliuose. Tai reiškia, kad tas pats lūkesčių impulsas sukelia mažesnį kainų lygio atsaką, kai lūkesčiai grindžiami suvokta, o ne faktine infliacija. Kiekybiškai tai pasireiškia trumpesniu reakcijos laikotarpiu ir mažesne piko amplitude. Apibendrinant, skirtingos Carlson–Parkin specifikacijos nekeičia pagrindinių makroekonominių ryšių ženklų, tačiau reikšmingai veikia jų intensyvumą ir patvarumą, ypač per vartotojų pasitikėjimo ir finansinio elgesio kanalus. Sentimento reakcijos yra jautriausios lūkesčių matavimo būdui, o tai reiškia, kad empirinės išvados apie infliacijos lūkesčių vaidmenį gali skirtis priklausomai nuo pasirinktos CP kalibracijos. Tai turi tiesioginių implikacijų tiek infliacijos prognozavimui, tiek lūkesčių įtraukimui į makroekonominės politikos analizę.

4.4. Vektorinė autoregresija atskirose šalyse

Atskirų šalių VAR analizė atskleidžia didelį heterogeniškumą infliacijos lūkesčių poveikio kanaluose, kuris yra gerokai paslėptas PVAR rezultatuose. Iš dvidešimt šešių analizuotų šalių tik šešios (CY, DE, EE, FI, IE, SE) rodo teigiamą realaus vartojimo reakciją į infliacijos lūkesčių šoką ir tik Suomijoje šis poveikis išlieka ilgiau nei 1–2 ketvirčius. Daugumoje šalių (18 iš 26) vartojimo reakcija yra statistiškai nereikšminga, o neigiamos reakcijos

neužfiksuojamos nė vienoje šalyje. Tai ryškiai kontrastuoja su paneliniu modeliu, kuriame fiksuojamas nedidelis (~0.4 proc. punkto), bet statistiškai reikšmingas vartojimo padidėjimas, trunkantis iki 3 ketvirčių. Infliacijos reakcijos į infliacijos lūkesčių šoką yra labiau vienalytės. 19 iš 26 šalių fiksuojamas teigiamas infliacijos atsakas, dažniausiai kupolo formos, su piku po 2–4 ketvirčių, atitinkantis panelinio modelio rezultatus. Trijose šalyse (CZ, HU, IT) infliacijos reakcija yra uždelsta, o dviuose šalyse (NL, SI) – statistiškai nereikšminga. Nė viena šalis nerodo tiesioginės neigiamos infliacijos reakcijos ir tai patvirtina, kad infliacijos lūkesčių šokai dažniausiai paveikia kainų lygį, nors reakcijos laikas ir stiprumas skiriasi.

Darbo užmokesčio augimo kanalas yra silpniausias ir labiausiai fragmentuotas, 20 iš 26 šalių nefiksuojamas statistiškai reikšmingas darbo užmokesčio atsakas. Tik dvi šalys (EE, HU) rodo tiesioginį teigiamą poveikį, Belgijoje stebimas uždelstas teigiamas efektas, o Ispanijoje nustatomas statistiškai reikšmingas neigiamas atsakas. Net ir šiais atvejais reakcijų dydžiai yra riboti ir gerokai mažesni, nei infliacijos ar vartojimo reakcijos, patvirtinant, kad atlyginimų-kainų spiralė nėra dominuojantis mechanizmas daugumoje ES šalių. Vartotojų pasitikėjimo indeksas reaguoja nuosekliausiai neigiama kryptimi, 18 iš 26 šalių fiksuojama tiesioginė neigiama reakcija, dar trijose šalyse (FI, NL, SE) – uždelsta neigiama reakcija ir tik Estijoje nustatomas trumpalaikis teigiamas poveikis. Airijoje reakcija yra statistiškai nereikšminga. Neigiami pasitikėjimo efektai dažniausiai išnyksta per 2–3 ketvirčius, o ilgiau nei 3 ketvirčius išlieka tik maždaug pusėje šalių ir tai rodo mažesnę patvarumą nei paneliniame modelyje. Šie rezultatai aiškiai rodo, kad panelinis PVAR vidurkina labai skirtingus nacionalinius mechanizmus. Nors bendros kryptys dažnai sutampa, reakcijų stiprumas, reikšmingumas ir patvarumas labai skiriasi tarp šalių. Todėl agreguoti paneliniai rezultatai gali pervertinti infliacijos lūkesčių realų efektą kai kuriose ekonomikose ir nepakankamai atskleisti struktūrinius skirtumus tarp šalių.

Lentelė 2. Atrinktų makroekonominų kintamųjų VAR impulso atsako funkcijų santrauka, reaguojant į teigiamą infliacijos lūkesčių (BS_YOY) šoką atskirose šalyse.

	Neigiamas atsakas	Vėluojantis neigiamas atsakas	Nėra reikšmingo atsako	Vėluojantis teigiamas atsakas	Teigiamas atsakas
Realaus vartojimo augimo tempas (CONS_YOY)	-	-	AT, BE, BG, CZ, ES, FR, GR, HR, HU, IT, LT, LU, NL, PL, PT, RO, SI, SK	-	CY, DE, EE, FI, IE, SE
Infliacija (PI_YOY)	-	-	NL, SI	CZ, HU, IT	AT, BE, BG, CY, DE, EE, ES, FI, FR, GR, HR, IE, LT, LU, PL, PT, RO, SE, SK
Darbo užmokesčio augimo tempas (WAGES YOY)	-	ES	AT, BG, CY, CZ, DE, FI, FR, GR, HR, IE, IT, LT, LU, NL, PL, PT, RO, SE, SI, SK	BE	EE, HU
Vartotojų pasitikėjimo indeksu pokytis (CCI YOY)	AT, BE, BG, CY, CZ, DE, ES, FR, GR, HR, HU, IT, LT, LU, PL, PT, RO, SI, SK	FI, NL, SE	IE	-	EE

4.5. Baigiamosios pastabos

Šis tyrimas atskleidžia, kad vartotojų infliacijos lūkesčių tikslus modeliavimas yra itin svarbus makroekonominėje analizėje ir išryškina kelis esminius aspektus. Pirma, nustatomas reikšmingas ryšys tarp infliacijos lūkesčių ir vartojimo elgsenos, atitinkantis teoriniuose modeliuose aprašytą tarplaikinio pakeičiamumo efektą. Impulsų–atsako analizė atskleidžia teoriškai nuoseklius, tačiau empiriškai riboto dydžio infliacijos lūkesčių poveikius agreguotai paklausai ir faktinei infliacijai. Taip pat svarbus rezultatas yra nuolatinis atlyginimų–kainų spiralės nebuvimas analizuotu laikotarpiu, rodantis ribotą infliacijos lūkesčių perdavimą į darbo užmokesčio dinamiką. Be to, priešingai nei prognozuoja tradicinė Phillips kreivė, nedarbo šokai turėjo tik menką poveikį infliacijai ir tai gali indikuoti struktūrines darbo rinkos ypatybes, tokias kaip nedarbo lygis, viršijantis natūralų nedarbo lygį.

Šie rezultatai taip pat gali reikšti, kad nagrinėtu laikotarpiu infliaciją labiau lėmė pasiūlos pusės šokai nei paklausos veiksniai.

Jautrumo analizė, taikant skirtingus kokybinių infliacijos lūkesčių kiekybinimo metodus parodė, kad nustatyti makroekonominiai ryšiai yra ypač susiję su vartotojų nuotaikomis ir vartojimo elgsena bei priklauso nuo pasirinktų metodologinių sprendimų. Tyrimas atskleidžia, kad vartotojų nuotaikų dinamika yra ypač jautri infliacijos lūkesčių kiekybinimo metodui. Todėl tyrimuose, analizuojančiuose vartotojų nuotaikas, būtina atsargiai rinktis infliacijos lūkesčių kiekybinimo metodą arba tikrinti rezultatų patikimumą taikant kelias alternatyvias specifikacijas. Galiausiai nustatoma, kad vartotojų infliacijos lūkesčių dinamika ir jų poveikis ekonomikai yra labai heterogeniški tarp šalių. Dėl šios priežasties tiksliausi rezultatai gaunami analizuojant vartotojų elgsenos ir makroekonomikos sąveiką individualių šalių kontekste.

5. SOCIODEMOGRAFINIS HETEROGENIŠKUMAS: KIEKYBINIMAS PAGAL POGRUPIUS IR TIKSLUMO GERINIMAS

Ankstesni tyrimai rodo, kad vartotojų infliacijos suvokimai ir lūkesčiai pasižymi sisteminiu teigiamu šališkumu, t. y. namų ūkiai yra linkę pervertinti faktinę infliaciją, lyginant su oficialiais rodikliais. Be to, nustatomas ryškus heterogeniškumas tarp individų, susijęs su amžiumi, pajamomis, išsilavinimu, lytimi ir asmenine infliacijos patirtimi. Europos Komisijos Verslo ir vartotojų apklausų duomenys leidžia šį heterogeniškumą analizuoti pogrupių lygmeniu. Taikant Carlson–Parkin metodą, galima pirmiausia kiekybinti infliacijos suvokimus ir lūkesčius pogrupių lygiu, o tik po to juos agreguoti. Toks dviejų etapų metodas leidžia koreguoti pogrupių specifinius šališkumus dar prieš agregaciją ir taip gauti tikslesnius infliacijos lūkesčių įverčius.

Šis požiūris iš esmės skiriasi nuo įprastai empiriniuose tyrimuose taikomos praktikos, kuomet heterogeniškumas dažniausiai yra ignoruojamas dėl ankstyvos agregacijos. Kiek žinoma, tai yra pirmasis bandymas akademinėje literatūroje sistemingai koreguoti pogrupių variaciją, kiekybinant vartotojų infliacijos suvokimus ir lūkesčius, prieš agreguojant atsakymus. Tolesnė analizė apima Lietuvos namų ūkių duomenis ir metodikos pritaikymą euro zonos mastu, vertinant kiekybinio tikslumo pagerėjimą, pasiektą atsižvelgiant į socio-demografinį heterogeniškumą.

5.1. Lietuvos namų ūkių duomenys

Lietuvos namų ūkių analizė, paremta 2011–2025 m. laikotarpio duomenimis, atskleidžia ryškų amžiaus heterogeniškumą infliacijos suvokime, tačiau gerokai silpnesnius skirtumus infliacijos lūkesčiuose. Jauniausioje amžiaus grupėje (15–29 m.) didžiąją laikotarpio dalį fiksuojamas žemiausias suvokiamos infliacijos lygis. Tuo metu 50–64 m. ir 65+ grupės pasižymi beveik identiška ir aukštesne suvoktos infliacijos dinamika. Pastarojo infliacijos šuolio metu skirtumai tarp grupių sumažėjo, o AGE2–AGE4 suvokimai judėjo beveik lygiagrečiai.

Infliacijos lūkesčių (Q6) balanso rodikliai rodo, kad visos amžiaus kohortos formuoja panašius lūkesčius, o AGE1 nukrypimai žemyn yra nedideli ir trumpalaikiai. Tai rodo, kad amžius labiau veikia retrospektyvius vertinimus nei į ateitį nukreiptus kainų lūkesčius.

Vartotojų pasitikėjimo rodiklis aiškiai diferencijuojasi pagal amžių: jaunesni namų ūkiai yra sistemiškai optimistiškesni, AGE2 užima tarpinę poziciją, o vyresnės kohortos išlieka labiausiai pesimistinės visame laikotarpyje. Ilgalaikio vartojimo lūkesčiai (Q9) pradžioje beveik nesiskiria, tačiau laikui bėgant išryškėja aiški divergencija: AGE1–AGE2 vis dažniau planuoja didinti išlaidas, o AGE3–AGE4 rodo vis santūresnius vartojimo ketinimus. Tai patvirtina, kad vartojimo sprendimai priklauso ne tik nuo makroekonominių sąlygų, bet ir nuo gyvenimo ciklo logikos.

Pajamų pagrindu išskaidyti duomenys rodo ryškesnį heterogeniškumą, lyginant su amžiaus kategorija. Aukščiausio pajamų kvartilio namų ūkiai (INCOME4) beveik visą laikotarpį pasižymi žemiausiais suvokiamos infliacijos lygiais, mažesniais infliacijos lūkesčiais ir aukščiausiu vartotojų pasitikėjimu. Tuo metu tarp trijų žemesnių pajamų grupių, infliacijos lūkesčių dinamika yra labai panaši ir tai rodo, kad pajamos stipriai diferencijuoja infliacijos suvokimą, bet pačius infliacijos lūkesčius – mažiau. Vartotojų pasitikėjimo rodiklis aiškiai didėja kartu su pajamomis ir išlieka sistemiškai aukštesnis INCOME4 grupėje beveik visą laikotarpį. Ilgalaikio vartojimo planai taip pat griežtai diferencijuojasi: INCOME1 grupėje teigiami lūkesčiai yra reti, o INCOME4 grupėje – dažni ir ilgalaikiai, signalizuojantys didesnę vartojimo potencialą. Vidurinių pajamų kvartilių (INCOME2–INCOME3) trajektorijos didžiąją laiko dalį persidengia, o nukrypimai yra trumpalaikiai.

Išskaidymas pagal išsilavinimą atskleidžia santykinai silpną heterogeniškumą, ypač lyginant su amžiaus ar pajamų pogrupiais. Žemesnio (EDUC1) ir vidutinio (EDUC2) išsilavinimo grupių infliacijos suvokimų ir lūkesčių balanso rodikliai pasižymi beveik identiška dinamika, o nedideli vidurkių skirtumai nėra sisteminio pobūdžio. Didžiausi skirtumai tarp EDUC1

ir EDUC2 pasireiškia ilgalaikio vartojimo planuose: EDUC1 grupėje balanso rodiklių dispersija yra gerokai didesnė ir indikuoja didesnę lūkesčių nepastovumą ir jautrumą ekonominiams svyravimams. Aukštąjį išsilavinimą turintys respondentai (EDUC3) dažniau pasižymi optimistiškesniais vertinimais namų ūkių finansų, bendros ekonominės situacijos ir vartotojų pasitikėjimo atžvilgiu, tačiau infliacijos lūkesčiai reikšmingai nesiskiria nuo kitų grupių ir šis optimistiškesnis vertinimas nėra stabilus laiko perspektyvoje.

Apskritai, išsilavinimas daro ribotą ir nenuoseklų poveikį infliacijos suvokimams, lūkesčiams ir pasitikėjimui, o jo reikšmė yra silpnesnė, lyginant su amžiaus ar pajamų. Tai rodo, kad nors išsilavinimas gali veikti per informacijos ir finansinio raštingumo kanalus, jis nėra pagrindinis heterogeniškumo šaltinis vartotojų infliacijos lūkesčiuose.

Išskaidymas pagal lytį atskleidžia mažiausią heterogeniškumo laipsnį tarp visų nagrinėtų pogrupių. Vyrai vidutiniškai pateikia šiek tiek optimistiškesnius vertinimus, lyginant su moterimis, tačiau šis skirtumas yra nedidelis, o daugeliu laikotarpių vyrų ir moterų balanso rodiklių trajektorijos beveik visiškai sutampa. Tai ypač būdinga infliacijos lūkesčiams (Q6) ir ilgalaikio vartojimo planams (Q9), kur ilgais laikotarpiais skirtumai išnyksta. Palyginti su pajamų ar amžiaus kohortomis, lytis turi tik epizodinį ir nesisteminę poveikį infliacijos suvokimams, lūkesčiams ir vartotojų pasitikėjimui. Nors moterys dažniau pateikia atsargesnius vertinimus, šis efektas neturi reikšmingos praktinės įtakos kiekybinei lūkesčių analizei.

Rezultatų interpretaciją riboja tai, kad analizė atliekama agreguotų pogrupių lygiu, todėl identifikuojamos koreliacijos, bet ne priežastiniai ryšiai. Persidengiančios demografinės charakteristikos, pavyzdžiui, didesnė moterų dalis vyresnio amžiaus grupėse, gali iškreipti pogrupių palyginimus. Vis dėlto, net ir esant šiems apribojimams, lyties pagrindu išskaidyta analizė rodo, kad heterogeniškumas pagal lytį yra ribotas ir antraeilis, palyginti su kitais socio-demografiniais veiksniais.

5.2. Carlson–Parkin metodo taikymas pogrupių duomenims

Namų ūkių apklausų atsakymų heterogeniškumas sudaro prielaidas taikyti naują Carlson–Parkin (CP) tikimybinio metodo panaudojimo būdą, skirtą vartotojų infliacijos suvokimų ir lūkesčių kvantifikavimui. Ankstesni tyrimai nuosekliai rodo, kad namų ūkiai pasižymi sisteminiu infliacijos suvokimų ir lūkesčių šališkumu, o Lietuvos vartotojai pagal pesimizmo lygį priskiriami prie labiausiai pesimistiškų respondentų Europos Sąjungoje. Remiantis šiomis įžvalgomis, tyrime siūloma kiekybinimo procedūrą patobulinti pasitelkiant pogrupių lygmens duomenis. Konkrečiai, pogrupis, kuriam būdingas

mažiausias balanso rodiklis, laikomas referenciniu ir kiekybinamas darant prielaidą apie normalųjį skirstinį. Likę pogrupiai kiekybinami naudojant necentrinį t skirstinį, kurio necentrališkumo parametras apibrėžiamas toliau pateikta išraiška. Sukiekybinus visų pogrupių infliacijos suvokimus arba lūkesčius, gauti rezultatai agreguojami taikant populiacijos svorius. Kiekvieno pogrupio svoris nustatomas pagal jo santykinę dalį bendroje populiacijoje, pavyzdžiui, atitinkamos amžiaus grupės gyventojų procentinę dalį:

$$ncp = \frac{BS_1 - BS_2}{SE_{(BS_1 - BS_2)}} \quad (2)$$

Kur BS_1 žymi santykinai labiau pesimistiško pogrupio balanso statistikos rodiklį ($/100$), o BS_2 – referencinio pogrupio balanso rodiklį ($/100$).

Kadangi analizėje naudojamos keturios pogrupių klasifikacijos – amžius, pajamos, išsilavinimas ir lytis – gaunami keturi skirtingi agreguotų rodiklių rinkiniai. Galutiniame etape šie pogrupiais pakoreguoti rodikliai lyginami su kanoniniu Carlson–Parkin metodo taikymu, kai normalusis skirstinys tiesiogiai pritaikomas agreguotiems apklausos atsakymams. Abiejų metodų santykinis tikslumas vertinamas lyginant RMSE reikšmes. Kiekybinimo procese mastelio parametru pasirenkamas faktinis metinis infliacijos lygis: suvokimams – π_{t-13} , lūkesčiams – π_{t-1} . Atsižvelgiant į tai, kad heterogeniškumas yra ryškesnis Lietuvos vartotojų infliacijos suvokimuose, siūlomas metodas pirmiausia taikomas penkto klausimo (Q5) atsakymų kvantifikavimui. Infliacijos lūkesčių (Q6) atveju, metodas taikomas euro zonos duomenims, kur pogrupių heterogeniškumas yra didesnis ir sudaro tinkamesnes sąlygas šio metodinio sprendimo patikrinimui.

5.3. Pogrupių duomenų kiekybinimo rezultatai

5.3.1. Lietuvos namų ūkių infliacijos suvokimai (Q5)

Rezultatai rodo, kad pogrupių pagrindu atliktas kiekybinimas reikšmingai pagerina infliacijos suvokimų tikslumą, lyginant su kanoniniu Carlson–Parkin metodu, taikomu agreguotiems duomenims. Visos imties laikotarpiu (2011.01–2025.05) kanoninio metodo RMSE siekia 6,779, tuo tarpu pogrupiais pakoreguoti rodikliai sumažina paklaidą iki 4,959–5,505 intervalo. Didžiausi tikslumo priaugiai gaunami skaidant pagal pajamas ir amžių, kur RMSE santykiei atitinkamai sudaro 1,367 ir 1,365, t. y. apie 36–37 % didesnis tikslumas. Skaidymas pagal išsilavinimą ir lytį taip pat pagerina rezultatų tikslumą, tačiau mažesniu mastu (RMSE santykiei 1,282 ir 1,231). Iki-pandeminiu laikotarpiu (2011.01–2019.12) bendras paklaidų lygis yra

mažesnis, tačiau pogrupių heterogeniškumo įtraukimas išlieka naudingas. Kanoninio CP metodo RMSE siekia 1,749, o pogrupiais pagrįsti metodai sumažina jį iki 1,471–1,529. Didžiausi tikslumo priaugiai vėl pasiekiami skaidant pagal pajamas (1,189), labai panašūs rezultatai gaunami skaidant pagal amžių (1,179) ir išsilavinimą (1,173). Tai rodo, kad net stabilios infliacijos laikotarpiais pogrupių heterogeniškumo koregavimas sistemingai didina kiekybinimo tikslumą.

Lentelė 3. Sukiekybinto Lietuvos vartotojų infliacijos suvokimo tikslumas.

LT Q5	CP agreguotiems duomenims	Amžiaus pogrūpių agregavimo rezultatas	Pajamų pogrūpių agregavimo rezultatas	Išsilavinimo pogrūpių agregavimo rezultatas	Lyties pogrūpių agregavimo rezultatas
Imtis 2011.01-2025.05					
RMSE vertė	6.779	4.965	4.959	5.287	5.505
RMSE santykis	-	1.365	1.367	1.282	1.231
Imtis 2011.01-2019.12					
RMSE vertė	1.749	1.483	1.471	1.491	1.529
RMSE santykis	-	1.179	1.189	1.173	1.144

5.3.2. Euro zonos namų ūkių infliacijos lūkesčiai (Q6)

Euro zonos duomenyse pogrupių lūkesčių heterogeniškumas yra ryškesnis, todėl siūlomo metodo taikymas taip pat rodo nuoseklų tikslumo padidėjimą. Visos imties laikotarpiu (2011.01–2025.05) kanoninio CP metodo RMSE yra 2,901, o pogrupiais pakoreguoti rezultatai sumažina paklaidą iki 2,324–2,534. Skaidymas pagal amžių pagerina tikslumą apie 14,5 % (RMSE santykis 1,145), tačiau didesni priaugiai gaunami skaidant pagal pajamas (1,217), išsilavinimą (1,233) ir lytį (1,248).

Iki-pandeminiu laikotarpiu (2011.01–2019.12) rezultatai tampa labiau diferencijuoti. Skaidymas pagal amžių negerina tikslumo (RMSE santykis 0,981), tačiau kiti pogrupiai vis dar reikšmingai pranoksta kanoninį metodą. Didžiausi tikslumo priaugiai fiksuojami skaidant pagal išsilavinimą (1,290) ir lytį (1,284), o kiek mažesni – pagal pajamas (1,131). Tai rodo, kad net mažo nepastovumo aplinkoje tam tikri socio-demografiniai pjūviai išlieka informatyvūs kvantifikuojant infliacijos lūkesčius.

Pogrūpių lygmeniu atliktas infliacijos suvokimų ir lūkesčių kiekybinimas su vėlesne agregacija naudojant populiacijos svorius, nuosekliai mažina RMSE, lyginant su kanoniniu Carlson–Parkin metodu. Didžiausias tikslumo padidėjimas pasiekiamas tada, kai heterogeniškumas yra ryškiausias – Lietuvos atveju pagal pajamas ir amžių, o euro zonoje – pagal išsilavinimą ir lytį. Tyrimo rezultatai rodo, kad pogrūpių heterogeniškumo koregavimas prieš agregavimą yra metodologiškai reikšmingas CP metodo išplėtimas, turintis aiškia empirinę naudą infliacijos lūkesčių ir suvokimų matavime.

Lentelė 4. Sukiekybintų euro zonos vartotojų infliacijos lūkesčių tikslumas.

EA Q6	CP agreguotiems duomenims	Amžiaus pogrūpių agregavimo rezultatas	Pajamų pogrūpių agregavimo rezultatas	Išsilavinimo pogrūpių agregavimo rezultatas	Lyties pogrūpių agregavimo rezultatas
Imtis 2011.01-2025.05					
RMSE vertė	2.901	2.534	2.384	2.353	2.324
RMSE santykis	-	1.145	1.217	1.233	1.248
Imtis 2011.01-2019.12					
RMSE vertė	0.994	1.013	0.879	0.770	0.774
RMSE santykis	-	0.981	1.131	1.290	1.284

5.4. Baigiamosios pastabos

Šiame skyriuje pagrindžiama, kad pogrūpių heterogeniškumo įtraukimas reikšmingai pagerina vartotojų infliacijos suvokimų ir lūkesčių kiekybinimą. Lietuvos duomenys rodo, jog Carlson–Parkin metodo taikymas pogrūpių lygmeniu ir vėlesnis rezultatų agregavimas, naudojant populiacijos svorius leidžia ženkliai sumažinti RMSE, lyginant su kanoniniu metodu, taikomu agreguotiems atsakymams. Didžiausias tikslumo padidėjimas pasiekiamas, skaidant pogrūpius pagal pajamas ir amžių. Tai parodo, kad būtent šie socio-demografiniai veiksniai yra svarbiausi formuojant infliacijos suvokimus. Euro zonos analizė patvirtina šių rezultatų reikšmingumą platesniame kontekste, čia didžiausias tikslumo padidėjimas pasiekiamas skaidant pogrūpius pagal išsilavinimą ir lytį, net ir santykinai stabilios infliacijos laikotarpiais. Tai rodo, kad pogrūpių pagrindu atliekama kvantifikacija pagerina infliacijos lūkesčių matavimą ne tik didelio nepastovumo, bet ir žemos infliacijos aplinkoje. Pogrūpių kiekybinimo nauda neapsiriboja vien RMSE sumažėjimu. Atskiras

CP metodo taikymas skirtingoms demografinėms grupėms leidžia išsaugoti dispersiją, kuri prarandama naudojant agreguotus rodiklius. Šis detalumas yra svarbus ekonominės politikos kontekste, nes leidžia tiksliau nustatyti, kurios gyventojų grupės labiausiai nukrypsta nuo faktinės infliacijos dinamikos ir kurioms gali būti reikalinga diferencijuota komunikacija.

Nors šis metodas neleidžia identifikuoti elgsenos mechanizmų ar tikslų heterogeniškumo šaltinių, nustatyti tikslumo pagerėjimai rodo, kad agregavimas paslepia reikšmingą duomenų struktūrą. Todėl pogrupių pagrindu gauti infliacijos suvokimų ir lūkesčių rodikliai geriau atspindi realią vartotojų percepciją, nei vien tik agreguotos priemonės. Ši analizė remiasi pogrupių lygmeniu agreguotomis balanso statistikomis, todėl neleidžia atskirti persidengiančių demografinių efektų. Be to, statiški pogrupių apibrėžimai, ypač pajamų atveju, nevisiškai atspindi asmenų judėjimą tarp grupių laikui bėgant. Vis dėlto, šie veiksniai greičiau mažina nei didina skaidymo naudą, todėl nustatyti tikslumo pridaugiai gali būti laikomi apatine riba. Šis metodas taip pat yra lengvai pritaikomas kitoms šalims ir apklausų sistemoms, o jo taikymas prognozavimo uždaviniuose išlieka svarbia tolesnių tyrimų kryptimi.

IŠVADOS

Šios disertacijos motyvacija kyla iš paprastos, tačiau nuolat pasikartojančios ekonomikos mokslo problemos: nors infliacijos lūkesčiai yra esminiai tiek teorijoje, tiek ekonominėje politikoje, jų matavimas ir interpretavimas nevienareikšmis. Šiame darbe pastaroji problema nagrinėjama tiek metodologiniu, tiek empiriniu požiūriu. Analizuojama, kaip formuojasi infliacijos lūkesčiai, kaip jie gali būti kiekybiškai įvertinti ir kokį vaidmenį atlieka infliacijos dinamikoje, ypač Baltijos šalių ir Europos Sąjungos kontekste. Dėmesys Baltijos šalims ir Europos Sąjungai grindžiamas tiek turiniais, tiek metodologiniais argumentais. Baltijos valstybėms būdinga infliacijos dinamika, kuri ryškiai skiriasi nuo platesnės euro zonos: vidutinė infliacija ir jos nepastovumas istoriškai čia nuolat buvo didesni, o vartotojų balansų statistika rodo sistemingai silpnesnę suderinamumą su faktine infliacija, nei euro zonos agreguotose duomenyse. Šios savybės leidžia daryti prielaidą, kad namų ūkiai formuoja infliacijos lūkesčius didesnio neapibrėžtumo sąlygomis, todėl šis regionas tampa itin palankiu Carlson–Parkin metodo patikimumui vertinti. Baltijos šalių rezultatų įterpimas į platesnę ES kontekstą, leidžia atlikti tiesioginį palyginimą su ekonomikomis, kuriose infliacijos lūkesčiai įprastai yra stabilesni ir tyrimuose yra tradiciškai taikomas CP metodas. Ši dvejopa prieiga suteikia prasmingą galimybę

patikrinti, ar plačiai naudojami kiekybinio vertinimo metodai išlieka nuoseklūs heterogeniškose ekonominėse aplinkose ir ar šalių specifinės struktūrinės ypatybės reikšmingai veikia lūkesčių formavimąsi bei kiekybinimą.

Apibendrinus metodologinės analizės, Baltijos šalių empirinės medžiagos ir ES šalių panelinės analizės rezultatus, galima išskirti šias pagrindines išvadas:

1. Nors CP metodas išlieka vyraujantis, jo tradicinės prielaidos – ypač lūkesčių normalusis pasiskirstymas ir simetriški indiferentiškumo intervalai – yra vis dažniau kvestionuojamos. Tuo pat metu nauji duomenų šaltiniai, tokie kaip ECB vartotojų lūkesčių apklausa ir eksperimentiniai dizainai, paremti atsitiktinių imčių kontroliuojamais tyrimais, plečia galimybes tirti infliacijos lūkesčius. Šis metodologinis kontekstas sudaro pagrindą šiame darbe taikomoms empirinėms strategijoms.
2. Nors nenormalūs pasiskirstymai gali geriau atspindėti duomenų asimetriją, prognozinio tikslumo pagerėjimas daugumoje imčių buvo nedidelis. Šios išvados atskleidžia tiek metodologinių patobulinimų naudą, tiek jų ribotumą. Analizė taip pat parodė, kad mastelio parametro pasirinkimas darė didesnę įtaką prognozių tikslumui nei pasiskirstymo pasirinkimas, pabrėžiant sukiekybintų lūkesčių metodologinį jautrumą. Šiame tyrime sistemingai analizuojamas vartotojų infliacijos lūkesčių įvertinamas Baltijos šalyse, kurios dažnai nėra įtraukiamos į lyginamuosius tyrimus. Tyrimas rodo, kad Baltijos šalių lūkesčiai yra labiau nepastovūs ir silpniau susiję su faktine infliacija nei euro zonoje. Todėl galima teigti, kad infliacijos lūkesčiai formuojasi nacionalinio konteksto sąlygomis ir kad vieningas matavimo metodas skirtingoms šalims gali užgožti svarbius skirtumus.
3. Vertinant orientuotumą į ateitį, Baltijos šalių vartotojai formuoja infliacijos lūkesčius trumpesniam laikotarpiui (apie 6–8 mėnesių), o ne 12 mėnesių horizontui. Be to, sukiekybintų lūkesčių prognozinės galios analizė parodė, kad jie retai pagerina infliacijos prognozavimo tikslumą, lyginant su paprastos balansų statistikos naudojimu.
4. Vartotojų lūkesčiai nėra dominuojantys infliacijos dinamikos variacijos šaltiniai. Daugumą stebimų svyravimų paaiškina pasiūlos šokai ir faktinė infliacija. Tačiau, infliacijos lūkesčiai turi reikšmės trumpalaikiam vartojimui ir atspindi namų ūkių pasitikėjimo rodiklį.

Šios išvados prisideda prie moksliniame diskurse besitęsiančios diskusijos, kurią paskatino Rudd (2021), kvestionuodamas centrinę infliacijos lūkesčių vaidmenį šiuolaikiniuose modeliuose. Gauti rezultatai leidžia teigti, kad infliacijos lūkesčiai yra svarbūs, tačiau jų vaidmuo yra labiau niuansuotas, sąlyginis ir priklausomas nuo konteksto, nei numato tradicinė teorija. Patikimumo patikros taip pat parodė, kad rezultatai yra jautrūs taikomam kiekybinimo metodui: mastelio parametrų pasirinkimas lėmė reikšmingus impulso atsako funkcijų rezultatų skirtumus. Kai kuriais atvejais, suvoktos, o ne faktinės infliacijos, naudojimas kaip mastelio parametro sustiprino įvertintą lūkesčių poveikį vartojimui ir infliacijai. Taip pat, buvo nustatytas reikšmingas heterogeniškumas tarp atskirų šalių.

5. Analizuojant pogrupių duomenis pagal amžių, pajamas, išsilavinimą ir lytį, išryškėja vartotojų infliacijos lūkesčių ir suvokimo heterogeniškumas. Carlson–Parkin metodo taikymas pogrupių lygmeniu ir vėlesnė agregacija, naudojant populiacijos svorius, nuosekliai pagerina prognozavimo tikslumą, lyginant su kanoniniu metodu agreguotiems duomenims. Lietuvoje didžiausi tikslumo pagerėjimai suvokiamoje infliacijoje nustatyti skaidant pagal pajamas ir amžių – tikslumas padidėjo daugiau nei 30 procentų, palyginti su standartinio metodo taikymu. Šios išvados patvirtintos ir euro zonos duomenimis, ypač ryškūs tikslumo pagerėjimai gauti atsižvelgiant į išsilavinimo ir lyties heterogeniškumą. Analizė taip pat atskleidė aiškius pogrupių dėsningumus: jaunesni namų ūkiai ir mažesnes pajamas gaunantys respondentai sistemingai nurodė žemesnę infliacijos suvokimą, o vyresnės kohortos pasižymėjo didesniu vidiniu suvoktos ir tikėtinos infliacijos nuoseklumu. Galima teigti, kad pogrupių heterogeniškumo pripažinimas ir įtraukimas leidžia ne tik tiksliau kiekybiškai įvertinti infliacijos lūkesčius, bet ir suteikia gilesnių įžvalgų apie socio-demografinius veiksnius, formuojančius namų ūkių infliacijos suvokimą.

Be empirinių rezultatų, disertacija pateikia ir keletą metodologinių indėlių į vartotojų infliacijos lūkesčių matavimą ir analizę.

- Lygindama alternatyvias Carlson–Parkin metodo specifikacijas ir balansinius rodiklius tame pačiame paneliniame VAR modelyje, disertacija parodo, kad kiekybinimo etape priimami metodologiniai sprendimai turi esminę įtaką įvertintoms impulsinėms reakcijoms ir dispersijos dekompozicijoms. Toks požiūris tiesiogiai susieja techninius lūkesčių matavimo aspektus su makroekonominėmis

išvadamis ir parodo, kad išvados apie lūkesčių vaidmenį infliacijos ir vartojimo dinamikoje yra jautrios tam, kaip kokybiniai apklausų duomenys paverčiami kiekybiniais rodikliais.

- Sukurtas ir įvertintas pogrupiais grindžiamas vartotojų infliacijos lūkesčių kiekybinimo metodas. Vietoj Carlson–Parkin metodo taikymo agreguotiems apklausų duomenims, disertacijoje lūkesčiai kiekybiškai įvertinami atskirai socialiniams ir demografiniams pogrupiams, o vėliau agreguojami naudojant gyventojų svorius. Parodoma, kad ši procedūra nuosekliai pagerina tikslumą, palyginti su kanoniniu agreguotu požiūriu, ir suteikia išsamesnių įžvalgų apie lūkesčių formavimąsi pagal amžiaus, pajamų, išsilavinimo ir lyties grupes. Gauti rezultatai rodo, kad heterogeniškumas nėra vien aprašomasis lūkesčių bruožas, bet dimensija, kuri gali būti tiesiogiai integruota į patį matavimo procesą.

Apibendrinant, šios disertacijos mokslinis indėlis yra trejopas. Pirma, pateikiamas kritinis Carlson–Parkin metodo ir jo alternatyvų vertinimas, atskleidžiant tiek metodologinių patobulinimų galimybes, tiek jų ribas. Antra, išplečiama empirinė bazė Baltijos šalių atžvilgiu ir pateikiama detali infliacijos lūkesčių dinamikos analizė šiose menkai ištirtose ekonomikose, įskaitant euro įvedimo vaidmenį. Trečia, prisidedama prie platesnės mokslinės diskusijos, pabrėžiant, kad vartotojų lūkesčiai turi ribotą infliacijos prognozinę galią, tačiau išlieka svarbūs namų ūkių nuotaikų ir vartojimo dinamikos rodikliai. Šių išvadų implikacijos yra tiek teorinės, tiek praktinės. Teoriniu požiūriu rezultatai palaiko riboto racionalumo ir riboto dėmesio modelius, kvestionuoja prielaidą, kad vartotojai formuoja nešališkus, į ateitį orientuotus lūkesčius, ir stiprina argumentus dėl elgsenos mechanizmų integravimo į makroekonominis modelius. Fiskalinės ir monetarinės politikos požiūriu, pabrėžiama centrinio banko komunikacijos ir patikimumo svarba: jei vartotojų lūkesčiai yra nepastovūs, šališki ir heterogeniški, jų valdymas labiau priklauso ne nuo techninių apklausų kiekybinio įvertinimo detalių, o nuo veiksmingų komunikacijos strategijų, kurios efektyviai perduoda informaciją toms visuomenės grupėms, kurių lūkesčių suvaldymas yra svarbesnis.

Kaip ir bet kuris empirinis tyrimas, ši disertacija turi tam tikrų apribojimų. Nors buvo nagrinėjamos alternatyvos kanoninėms Carlson–Parkin prielaidoms, tikslumo pagerėjimai dėl alternatyvių skirstinių taikymo buvo nedideli, o tai rodo ribotas grynai statistinių patobulinimų galimybes. Be to, analizė parodė, kad modelių rezultatai jautrūs mastelio parametrų, pasiskirstymo prielaidų ir agregavimo procedūrų pasirinkimui. Nors buvo atliktos patikimumo patikros, tokia priklausomybė nuo modeliavimo

sprendimų reiškia, kad išvadas reikia interpretuoti atsargiai. Skirtingi metodologiniai pasirinkimai gali lemti kiekybiškai skirtingus rezultatus, net jei kokybinės išvados iš esmės išlieka panašios. Empirinės analizės apimtis taip pat nustato savotiškas ribas: didžioji disertacijos dalis skirta Baltijos šalims, kurios pasižymi savitomis ypatybėmis. Galiausiai paminėtinas ir laiko periodo aspektas. Duomenys apima tiek vidutinės infliacijos laikotarpius, tiek pastarąjį didelės infliacijos šuolį. Nors tai suteikia galimybę testuoti lūkesčius labai skirtingose aplinkose, kartu tai reiškia, kad išvados yra susietos su konkrečių epizodų dinamika.

Ateities tyrimai galėtų plėtoti šią analizę keliomis svarbiomis kryptimis. Pirma, empirinės analizės išplėtimas ilgesniems istoriniams laikotarpiams leistų įvertinti rezultatų stabilumą skirtinguose infliacijos režimuose ir makroekonominėse aplinkose, įskaitant užsitęsusios žemos infliacijos laikotarpius ir padidėjusio infliacinio spaudimo epizodus. Antra, tolesni tyrimai galėtų gilintis į vartotojų atsakymų heterogeniškumo šaltinius, atskiriant demografinius, socio-ekonominius ir informacinius veiksnius, taip pat nagrinėjant, ar heterogeniškumo struktūra ir ją lemiantys veiksniai sistemingai skiriasi tarp šalių. Trečia, ateities tyrimuose būtų tikslinga vertinti pogrupių pagrindu sudarytų infliacijos lūkesčių rodiklių dinamiką realiuoju laiku ir jų naudą pinigų politikos analizei lyginant su agreguotais rodikliais. Galiausiai, ateities tyrimai galėtų nagrinėti faktinį prognozavimo horizontą, kuriuo remiasi vartotojų infliacijos lūkesčiai, vertinant, ar respondentai iš tiesų formuoja 12 mėnesių laikotarpio lūkesčius, ar jų atsakymai atspindi trumpesnius ar kintamus horizontus, ir kaip horizontų heterogeniškumas veikia apklausomis pagrįstų lūkesčių rodiklius.

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