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SINARA DO VALLE

The Anatomy of Brazilian Inflation in Three Essays:
Regional Dynamics, Distributional Impact,
and the Role of Food Prices

Uberlândia – MG

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SINARA DO VALLE

**The Anatomy of Brazilian Inflation in Three Essays:
Regional Dynamics, Distributional Impact,
and the Role of Food Prices**

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EXAMINATION COMMITTEE:

Prof. Cleomar Gomes da Silva, Ph.D.
Advisor – (PPGE-UFU)

Prof. Fábio Augusto Reis Gomes, Ph.D.
Examiner – (FEA-RP/USP)

Prof. Gabriel Caldas Montes, Ph.D.
Examiner – (PPGE-UFF)

Prof. Michele Poline Veríssimo, Ph.D.
Examiner – (PPGE-UFU)

Prof. Julio Fernando Costa Santos, Ph.D.
Examiner – (PPGE-UFU)

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UNIVERSIDADE FEDERAL DE UBERLÂNDIA
Coordenação do Programa de Pós-Graduação em Economia

Av. João Naves de Ávila, nº 2121, Bloco 1J, Sala 218 - Bairro Santa Mônica, Uberlândia-MG, CEP 38400-902

Telefone: (34) 3239-4315 - www.ppge.ie.ufu.br - ppge@ufu.br


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Dedicated to my parents

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*“They that trust in the Lord shall be as mount Zion,
which cannot be removed, but abideth for ever.”*
(Psalm 125:1)

ABSTRACT

This thesis investigates the sources, transmission channels, and distributional consequences of Brazilian inflation across three essays covering the period 1999–2026, using panels disaggregated by expenditure category, metropolitan region, and household income. We test the hypothesis that a homogeneous treatment of the headline IPCA conceals structural heterogeneity that disaggregated econometric methods can uncover. The methodology combines the Multivariate Core Trend (MCT) of Almuzara and Sbordone (2022, 2024) with a Time-Varying Parameter VAR with Dynamic Connectedness (TVP-VAR-DY) and local projections to assess shock transmission and the monetary policy response, a Time-Varying Parameter (TVP) Phillips curve estimated via the Kalman filter, the Club Convergence approach of Phillips and Sul (2007, 2009), and a Univariate Unobserved Components Stochastic Volatility Outlier-adjusted (UCSVO) model. Results indicate that: (i) food inflation is structurally heterogeneous, with Food at Home displaying rising permanent volatility and outlier probabilities above 0.85 against a ceiling of 0.21 for Food Away From Home, while Food Away From Home propagates permanent shocks more intensely (88.33% versus 78.09%) and elicits a stronger Selic response despite its smaller basket weight; (ii) regional persistence varies markedly across the eleven metropolitan areas analyzed, with no global convergence in headline regional inflation but clear convergence in Household Items and Transportation; (iii) inflation inequality across income strata is regressive, as trend inflation is consistently higher and more volatile for lower-income households, whose outliers are also more frequent and severe; and (iv) transmission is highly asymmetric, with the output gap affecting lower-income inflation as early as 2008, more than a decade before its effect became evident in the headline index. This indicates that monetary policy calibrated solely on the aggregate IPCA risks responding too late, too uniformly, or too regressively to price dynamics that are, in fact, substantially heterogeneous. Ultimately, these findings establish that sectoral, regional, and distributional disaggregation is a technical requirement for improving the precision, timing, and fairness of monetary policy in Brazil.

Keywords: Inflation Persistence. Regional Convergence. Income Inequality. Food Inflation. Brazil.

JEL Classification: C32; E31; E52.

RESUMO

Esta tese investiga as fontes, os canais de transmissão e as consequências distributivas da inflação brasileira em três ensaios, abrangendo o período de 1999 a 2026, utilizando painéis desagregados por categoria de gasto, região metropolitana e renda domiciliar. Testa-se a hipótese de que um tratamento homogêneo do IPCA agregado oculta uma heterogeneidade estrutural que métodos econométricos desagregados são capazes de revelar. A metodologia combina o Multivariate Core Trend (MCT) de Almuzara e Sbordone (2022, 2024) com um VAR de parâmetros variantes no tempo com conectividade dinâmica (TVP-VAR-DY) e local projections para avaliar a transmissão de choques e a resposta da política monetária, uma Curva de Phillips de parâmetros variantes no tempo (TVP) estimada via filtro de Kalman, a abordagem de Convergência em Clubes de Phillips e Sul (2007, 2009), e um modelo univariado Unobserved Components Stochastic Volatility com ajuste para outliers (UCSVO). Os resultados indicam que: (i) a inflação de alimentos é estruturalmente heterogênea, com a Alimentação no Domicílio apresentando volatilidade permanente crescente e probabilidades de outliers acima de 0,85 contra um teto de 0,21 para a Alimentação Fora do Domicílio, ao passo que a Alimentação Fora do Domicílio propaga choques permanentes com maior intensidade (88,33% contra 78,09%) e provoca uma resposta mais forte da Selic apesar do menor peso na cesta; (ii) a persistência regional varia de forma expressiva entre as onze regiões metropolitanas analisadas, sem convergência global para a inflação regional agregada, mas com convergência clara em Itens de Habitação e Transporte; (iii) a desigualdade inflacionária entre os estratos de renda é regressiva, com a inflação de tendência consistentemente mais alta e mais volátil para as famílias de menor renda, cujos outliers também são mais frequentes e severos; e (iv) a transmissão é altamente assimétrica, com o hiato do produto afetando a inflação das famílias de menor renda já em 2008, mais de uma década antes de seu efeito se tornar evidente no índice agregado. Isso indica que a política monetária calibrada exclusivamente no IPCA agregado corre o risco de responder de forma tardia, uniforme ou regressiva demais a dinâmicas de preços que são, de fato, substancialmente heterogêneas. Em última análise, esses resultados estabelecem que a desagregação setorial, regional e distributiva constitui um requisito técnico para aprimorar a precisão, o tempo de resposta e a justiça social da política monetária no Brasil.

Palavras-chave: Persistência Inflacionária. Convergência Regional. Desigualdade de Renda. Inflação de Alimentos. Brasil.

Classificação JEL: C32; E31; E52.

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LIST OF ABBREVIATIONS AND ACRONYMS

ADF	Augmented Dickey-Fuller (unit root test)
ADF-GLS	Augmented Dickey-Fuller Generalized Least Squares (unit root test)
BCB	Banco Central do Brasil
BIS	Bank for International Settlements
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
CNPq	Conselho Nacional de Desenvolvimento Científico e Tecnológico
CODACE	Comitê de Datação de Ciclos Econômicos
COVID-19	Coronavirus Disease 2019
CPI	Consumer Price Index
DY	Diebold-Yilmaz
FA	Food Away From Home
FGV	Fundação Getúlio Vargas
FH	Food at Home
GFC	Global Financial Crisis
GMM	Generalized Method of Moments
GSCPI	Global Supply Chain Pressure Index
HAC	Heteroskedasticity and Autocorrelation Consistent
HP	Hodrick-Prescott (filter)
IBGE	Instituto Brasileiro de Geografia e Estatística
IERI-UFU	Institute of Economics and International Relations, Federal University of Uberlândia
IPCA	Índice de Preços ao Consumidor Amplo
IPEA	Instituto de Pesquisa Econômica Aplicada
JEL	Journal of Economic Literature
KPSS	Kwiatkowski-Phillips-Schmidt-Shin (stationarity test)

LP	Local Projections
MCMC	Markov Chain Monte Carlo
MCT	Multivariate Core Trend
MUCSVO	Multivariate Unobserved Components Stochastic Volatility with Outlier adjustment
NAIRU	Non-Accelerating Inflation Rate of Unemployment
NBER	National Bureau of Economic Research
NET	Net Directional Connectedness
NKPC	New Keynesian Phillips Curve
OLS	Ordinary Least Squares
PP	Phillips-Perron (unit root test)
POF	Pesquisa de Orçamentos Familiares
PPGE	Programa de Pós-Graduação em Economia
REER	Real Effective Exchange Rate
SIDRA	Sistema IBGE de Recuperação Automática
TCI	Total Connectedness Index
TVP	Time-Varying Parameter
TVP-NKPC	Time-Varying Parameter New Keynesian Phillips Curve
TVP-VAR	Time-Varying Parameter Vector Autoregression
TVP-VAR-DY	Time-Varying Parameter Vector Autoregression with Diebold-Yilmaz Connectedness
UCSVO	Unobserved Components Stochastic Volatility with Outlier adjustment
UFU	Universidade Federal de Uberlândia
VAR	Vector Autoregression
ZA	Zivot-Andrews (unit root test)

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1 GENERAL INTRODUCTION

The identification of the sources, transmission channels, and distributional consequences of inflation is one of the central questions of macroeconomics and monetary policy. Aggregate price indices average away a substantial amount of heterogeneity: across the items that compose the consumption basket, across the regions in which prices are formed, and across the households that bear the burden of rising prices. This raises questions that remain empirically unsettled for the Brazilian case. Which components of inflation are genuinely persistent, and which are merely volatile and mean reverting? Does the trajectory of national inflation adequately represent what happens across the country's regions? Does a single headline number describe the price experience of both the poorest and the wealthiest Brazilian households? In an inflation targeting regime such as Brazil's, anchored on the Extended National Consumer Price Index (IPCA) since the 1994 Real Plan, these questions have direct practical relevance, since the timing, magnitude, and distributional fairness of monetary policy depend on how well the headline index captures the underlying heterogeneity of the price formation process.

In this context, the disaggregation of inflation by expenditure category, by geographic region, or by household income group has become an important empirical strategy for uncovering dynamics that the aggregate index does not reveal. State space methods with stochastic volatility, time varying parameters, and nonlinear convergence tests allow permanent and transitory shocks to be separated, allow persistence to evolve over time rather than being assumed constant, and allow subgroups of a panel to gravitate toward distinct long run equilibria rather than a single common trend. Each of the three essays that compose this thesis applies this set of methods along a different type of disaggregation, sharing a common argument: while an aggregate treatment of Brazilian inflation provides a fundamental baseline, incorporating its internal composition further refines the analysis, thereby optimizing monetary policy decisions and mitigating the social impacts of economic policy.

The data requirements differ across these three axes, which shaped the choice of methodology and sample period for each essay. The disaggregation by expenditure category (Essay 1) uses the standard nine group IPCA classification released monthly by IBGE, covering the sample period from 1999 onward, further divided into Food at Home and Food Away From Home, which allows the longest available sample and the granularity required for a multivariate state space model. The regional disaggregation (Essay 2) draws on the eleven metropolitan area IPCA series compiled by IBGE, available from 2003 onward, combined with a set of macroeconomic controls at monthly frequency, which supports both a time varying Phillips curve and a club convergence analysis. The disaggregation by household income (Essay 3) relies on the income group IPCA series developed by IPEA, available from 2006 onward, whose univariate structure motivated the choice of an Unobserved Components Stochastic Volatility model rather than a multivariate one, a data limitation discussed explicitly in that essay's conclusion. Together,

these three sources of disaggregation, sectoral, spatial, and distributional, allow the thesis to examine Brazilian inflation from complementary perspectives, within the limits of what the underlying statistical infrastructure currently permits.

The recent literature on inflation dynamics has moved beyond the estimation of a single, homogeneous persistence parameter for the headline index, recognizing that trend, volatility, and inertia differ systematically across subcomponents of the price system. Building on this literature and on econometric methods suited to each dimension of disaggregation considered, the essays gathered in this thesis investigate, at three distinct scales, the sectoral composition of the consumption basket, the country’s metropolitan regions, and its household income strata, how heterogeneity in trend, volatility, and persistence shapes the transmission and distributional incidence of Brazilian inflation.

The first essay investigates food inflation persistence and volatility in Brazil from August 1999 to May 2026, testing the hypothesis that Food at Home and Food Away From Home follow structurally divergent dynamics that the standard practice of treating food shocks as uniformly transitory fails to capture. The methodology employs the Multivariate Core Trend (MCT) of Almuzara, and Sbordone (2022) and Almuzara, and Sbordone (2024) to jointly decompose the two subcomponents into permanent and transitory volatility with outlier adjustment, complemented by a Time Varying Parameter VAR with dynamic connectedness and local projections to assess the monetary policy response. The results show that Food at Home exhibits a growing permanent volatility component and a substantially higher outlier probability than Food Away From Home, while Food Away From Home, despite its smaller basket weight, transmits permanent shocks more intensely to the rest of the system and elicits a stronger Selic response. These findings indicate that a uniformly transitory treatment of food shocks based only on the headline index introduces a systematic bias in the assessment of underlying inflation.

The second essay examines inflation persistence and club convergence across eleven Brazilian metropolitan areas from January 2003 to November 2024. The empirical strategy combines a Time-Varying Parameter Phillips Curve, estimated via the Kalman filter, with the club convergence methodology of Phillips, and Sul (2007) and Phillips, and Sul (2009), applied both to headline regional inflation and to its eleven sectoral components. The results reveal pronounced heterogeneity in regional persistence, with Curitiba displaying high inertia and Salvador, Belém, and Brasília displaying comparatively low inertia, an asymmetry that the COVID-19 pandemic further accentuated in specific cities. While no global convergence is found for headline regional inflation, disaggregation by sector uncovers strong convergence in Household Items and Transportation, alongside weaker, transitional convergence patterns in Food and Communication. This evidence is consistent with an aggregation bias that conceals substantial subnational inertia behind the national index.

The third essay, investigates inflation inequality across four household income strata in Brazil, very low, low, middle, and high income, from July 2006 to April 2025, using the headline IPCA as a benchmark. The methodology combines a univariate Unobserved Components

Stochastic Volatility Outlier adjusted (UCSVO) model to characterize trend and volatility by income group with a Time Varying Parameter Phillips curve to assess persistence and macro-economic transmission. The results document a regressive pattern in Brazilian inflation. Trend inflation is consistently higher and more volatile for lower income households, whose inflation outliers are also more frequent and more severe, while inflation expectations anchor price setting almost exclusively for the high income group, and the output gap has influenced lower income inflation since 2008, more than a decade before its effect became statistically evident in the headline index. These findings indicate that a uniform monetary policy response calibrated to the aggregate IPCA may systematically arrive too late for the households least able to absorb its costs.

The thesis defended in this work rests on the premise that the effects of inflation on economic welfare and on the effectiveness of monetary policy cannot be adequately assessed through the headline index alone, but depend on how price dynamics are distributed across the sectoral, spatial, and social dimensions of the economy. Trend inflation, volatility, and persistence are not uniform properties of the price system. They vary systematically according to the structure of household consumption, the geography of markets, and the socioeconomic composition of the population, and this variation carries direct implications for the timing and the distributional fairness of monetary policy.

By articulating evidence across three complementary dimensions, sectoral, regional, and distributional, the study demonstrates that food inflation in Brazil is structurally heterogeneous rather than uniformly transitory, that regional price dynamics combine persistent local inertia with sector specific convergence rather than a single national pattern, and that the burden of inflation falls disproportionately on lower income households through both higher permanent volatility and a more frequent incidence of extreme shocks. Taken together, these results indicate that an inflation targeting regime anchored solely on the aggregate IPCA risks responding too late, too uniformly, or too regressively to price dynamics that are, in fact, substantially heterogeneous beneath the headline number.

Besides this introduction, the thesis presents the first essay in Chapter 2, the second essay in Chapter 3, and the third essay in Chapter 4, followed by the concluding remarks.

2 FOOD INFLATION PERSISTENCE AND VOLATILITY IN BRAZIL: A MULTIVARIATE CORE TREND APPROACH

Abstract

This article investigates food inflation persistence in Brazil from August 1999 to May 2026. We test the hypothesis that Food at Home and Food Away From Home exhibit structurally divergent persistence dynamics, challenging the standard practice of treating food shocks as uniformly transitory. The methodology employs the Multivariate Core Trend (MCT) of Almuzara, and Sbordone (2022) and Almuzara, and Sbordone (2024) to decompose trend and volatility, with seasonality incorporated endogenously through sector-specific priors and transitory shock persistence modeled through a moving-average process, followed by a Time-Varying Parameter VAR with dynamic connectedness (TVP-VAR-DY) and local projections to assess shock transmission and the monetary policy response. Results indicate that: (i) Food at Home shows rising permanent volatility, with trend peaks ranging from 14.25% to 24.83%; (ii) Food Away From Home shows the opposite pattern, with declining volatility and an outlier probability that never exceeds 0.21; (iii) the Selic transmits more volatility to the food system than it receives (a positive net position of +20.6%), while the permanent volatility of Food Away From Home is the component that most consistently absorbs volatility from the rest of the system (−23.9%); and (iv) the Selic reacts more strongly to Food Away From Home despite Food at Home’s larger basket weight. This indicates that treating food shocks as uniformly transitory introduces a systematic bias in assessing inflation persistence. Ultimately, these findings reveal that a disaggregated treatment of food inflation is necessary to prevent delayed monetary policy responses.

Keywords: Food Inflation; Multivariate Core Trend; TVP-VAR-DY; Local Projections.

JEL Classification: C32; E31; E52.

2.1 Introduction

The conventional wisdom in inflation dynamics holds that food price shocks are high-frequency, temporary supply-side disturbances. Under this standard view, central banks are advised to treat food price anomalies as highly volatile but strictly mean-reverting noise that does not alter the core trajectory of inflation or long-term expectations, looking past food episodes to focus the policy reaction function on a narrower, more stable price measure.

Food prices carry a large and historically stable weight in the Brazilian consumer price index, oscillating between 20% and 25% of the total basket. Under the household budget survey in force since January 2020, food at home accounts for approximately 15.75% of the index and food away from home for approximately 5.94%, totalling 21.69% for the group as a whole. Beyond this difference in scale, the two subcomponents have structurally distinct cost structures: food at home is directly exposed to agricultural commodity fluctuations and the exchange rate, while food away from home is determined primarily by labor costs, rent, and services, which respond more slowly to primary supply shocks.

In light of these structural differences, this paper addresses the following question: to what extent do the persistence, volatility, and transmission of food price shocks in Brazil differ between Food at Home and Food Away From Home, and is the practice of treating aggregate food shocks as uniformly transitory empirically justified? The central hypothesis is that food inflation in Brazil is structurally heterogeneous, with Food at Home exhibiting a growing permanent component that a headline-only monetary policy fails to detect, while Food Away From Home remains predominantly transitory but highly persistent once absorbed. Methodologically, the study employs the Multivariate Core Trend (MCT), developed at the Federal Reserve Bank of New York by Almuzara, and Sbordone (2022) and formalized in Almuzara, and Sbordone (2024), to jointly decompose Brazilian food and non-food inflation into permanent and transitory components with time-varying stochastic volatility and outlier adjustment. Its derivation proceeds in steps: Stock, and Watson (2016) extended the stochastic-volatility model of Stock, and Watson (2007), first to the univariate unobserved-component model with stochastic volatility and outlier correction, and then to its multivariate counterpart, which introduces a common factor structure with time-varying loadings across sectors; the multivariate core trend builds on this foundation by adding moving-average dynamics to the transitory component, allowing the model to capture the gradual dissipation of shocks in monthly data. As a complementary analysis, the connectedness structure among price groups is investigated using the time-varying parameter vector autoregression approach of Diebold, and Yilmaz (2009), Diebold, and Yilmaz (2012), and Antonakakis, Chatziantoniou, and Gabauer (2020), together with local projections (Jordà, 2005) to trace the monetary policy response.

This is the first application of the multivariate core trend to Brazilian data and to a food inflation disaggregation. The paper bridges this gap and contributes to the existing literature in three ways. First, it applies a state-space technique developed for macro-aggregates to the microstructural division of the food price basket, delivering a localized mapping of price transmission that aggregate models miss. Second, it demonstrates that food inflation in Brazil is no longer purely transitory, as part of each shock is permanently incorporated into the price trajectory, generating a structural shift in baseline inflation uncertainty. Finally, by covering the full 1999–2026 period, including multiple commodity cycles, two global financial dislocations, and the pandemic episode, it provides the most comprehensive empirical characterization of Brazilian food inflation dynamics to date.

The empirical findings confirm this hypothesis of a structural dichotomy between the two food subcomponents. The Multivariate Core Trend estimates show that the twelve-month accumulated trend of Food at Home reached peaks of 24.83% in May 2003 and 14.25% in July

2008, before falling to a trough of -3.06% in 2017 and rising again to 14.80% in February 2021, consistently and substantially above the corresponding peaks of Food Away From Home, with the latter lagging behind Food at Home by several months to a year in most episodes – though, in the Great Brazilian Recession, the timing reverses, with Food Away From Home peaking several months before Food at Home. The permanent volatility of Food at Home exhibits a secular upward trend over the sample, while that of Food Away From Home declines, indicating that the two subcomponents have moved in structurally opposite directions; the posterior outlier probability of Food at Home reaches values above 0.85 in several episodes, while that of Food Away From Home never exceeds 0.21 over the entire sample, confirming that the tradable subcomponent is far more exposed to large transitory disturbances that threaten to contaminate the permanent trend.

The complementary connectedness analysis shows that the Selic transmits more volatility to the food system than it receives (a positive net position of $+20.6\%$), while the permanent volatility of Food Away From Home is the component that most consistently absorbs volatility from the rest of the system (-23.9%), and that this transmission relationship strengthens considerably once food is split into its at-home and away-from-home components. The local projection exercise further shows that the Selic rate reacts more strongly to the permanent trend of Food Away From Home than to that of Food at Home despite the latter’s larger basket weight, consistent with monetary policy tracking the more persistent, service-linked price dynamics rather than the more volatile, commodity-linked ones.

In summary, these results demonstrate that permanent stochastic volatility in Food at Home has structurally elevated and plateaued at a higher baseline, transforming global climate risks and imported logistical bottlenecks from temporary supply noise into a variable that monetary authorities can no longer afford to ignore. Failing to react to these structurally embedded shocks risks allowing imported supply disruptions to contaminate broader services inflation, permanently unanchoring inflation expectations and demanding a structurally tighter monetary policy stance than traditional core models would prescribe. Ultimately, these findings reveal that a monetary policy strategy anchored solely on the headline IPCA risks responding too late to shocks in Food at Home that have already become embedded in the permanent trend, pointing to the need for income- and sector-disaggregated indicators in the design of monetary policy.

The remainder of this paper is organized as follows. Section 2.2 reviews the relevant literature. Section 2.3 describes the data. Section 2.4 presents the methodology. Section 2.5 discusses the main results. Section 2.6.1 presents the complementary connectedness analysis. Section 2.7 concludes.

2.2 Literature Review

The investigation of inflation persistence has a long tradition in macroeconomic literature. Cogley, and Sargent (2002) documented evidence that U.S. inflation persistence declined after the 1980s, attributing this change to shifts in the monetary policy regime. Pivetta, and Reis (2007) questioned this conclusion by constructing confidence intervals for persistence estimates, showing that uncertainty around the point estimates is sufficiently large to not reject the hypothesis of stability over time. Stock, and Watson (2007) proposed an alternative approach based on an unobserved-components model with stochastic volatility, in which the ratio between the volatilities of the permanent and transitory components varies over time, capturing changes in the difficulty of forecasting inflation without imposing parametric restrictions on the trajectory of persistence.

The literature on core inflation measures developed in parallel. Bryan, and Cecchetti

(1994) proposed the use of trimmed means as a robust measure of the inflation trend. Cecchetti (1997) proposed the use of dynamic factor models to estimate the common component of sectoral inflation, establishing a bridge between cross-sectional and time-series smoothing approaches. Stock, and Watson (2016) unified these lines of research by proposing the Unobserved Components Stochastic Volatility Outlier-adjusted (UCSVO) model, which separates inflation into a permanent trend and a transitory component, both with time-varying stochastic volatility, and incorporates an explicit mechanism for the detection and correction of large point deviations in the transitory component. Stock, and Watson (2016) also developed the multivariate extension of the UCSVO, the MUCSVO, which estimates a common factor structure with time-varying loadings across sectors jointly. Almuzara, and Sbordon (2022) further extended the MUCSVO to develop the Multivariate Core Trend (MCT), adding moving-average dynamics in the transitory component to capture the gradual dissipation of monthly shocks. Almuzara, Kocaoglu, and Sbordon (2023) launched the MCT as a regular product of the Federal Reserve Bank of New York. Almuzara, Jarocinski, and Sbordon (2023) used the model to dissect the layers of post-pandemic inflation persistence in the United States. Almuzara, Sbordon, et al. (2025) developed the MCT Global, showing that global factors explain up to 90% of consumer inflation persistence in seven advanced economies. Apergis (2025) applied the MCT to 23 U.S. metropolitan areas, finding persistence in ten of them.

In the Brazilian context, the literature on food inflation has primarily focused on descriptive characterization rather than formal econometric decomposition of persistence. Oliveira, Baccarin, and Costa (2025) characterized food inflation in Brazil between 2007 and 2022, documenting that Food at Home inflation was driven by agricultural supply conditions and international commodity linkages, while Food Away From Home responded more to domestic demand and labor market dynamics. The authors noted that the pandemic episode reversed the pre-2020 pattern in which Food Away From Home had expanded faster than Food at Home, but they did not formally separate permanent from transitory components. Regarding structural time-series models, Costa Filho (2023) employed a trend-cycle model with stochastic volatility to estimate Brazilian trend inflation from 2002 to 2022, documenting a sustained downward trajectory from 2017 and resilience against the pandemic surge. However, this analysis applies to the headline IPCA and does not disaggregate food subcomponents.

Tangza (2019) applied the MUCSVO model to Brazilian IPCA inflation from 2000 to 2019, showing that the structural trend became progressively less susceptible to idiosyncratic shocks, but again focused on the aggregate index. Valle, and Gomes da Silva (2026) investigated inflation inequality across four income groups in Brazil using the univariate UCSVO and a time-varying parameter Phillips Curve, documenting that trend inflation is persistently higher and more volatile among lower-income groups, who allocate a larger share of their budget to food. Gomes da Silva, Santos, and Valle (2026) investigated the impact of price disaggregation on the estimation of aggregate trend inflation and volatility in Brazil, providing direct motivation for the use of a disaggregated multivariate framework. To the best of our knowledge, no prior study has formally decomposed the permanent and transitory components of food inflation in Brazil at the level of Food at Home and Food Away From Home using a multivariate unobserved-components model.

This paper fills that gap. To characterize the direction and intensity of shock transmission across IPCA groups, the analysis also draws on the TVP-VAR framework with Generalized Forecast Error Variance Decomposition of Diebold, and Yilmaz (2009), Diebold, and Yilmaz (2012), and Diebold, and Yilmaz (2014), extended by Antonakakis, Chatziantoniou, and Gabauer (2020), which enables month-by-month tracking of the propagation of both permanent and transitory shocks.

2.3 Data

To achieve our goal of investigating inflation heterogeneity across expenditure groups in Brazil from August 1999 to May 2026 using the Multivariate Component Trend model (MCT), we consider the following variables:

- IPCA – Headline: National Consumer Price Index (monthly %). Source: Brazilian Institute of Geography and Statistics (IBGE).
- IPCA by Expenditure Group: Nine-group disaggregation (Food and Beverages, Housing, Household Items, Clothing, Transportation, Health and Personal Care, Personal Expenses, Education, and Communication), monthly %. Source: IBGE.
- IPCA – Food and Beverages, disaggregated: Ten-group specification splitting Food and Beverages into Food at Home and Food Away From Home, monthly %. Source: IBGE.
- IPCA Expectations: One-month-ahead expectations (seasonally adjusted). Source: Central Bank of Brazil (BCB).
- IBC-Br: Central Bank’s Economic Activity Index (logarithm, HP-filtered, seasonally adjusted). Source: BCB.
- REER: Real Effective Exchange Rate (logarithm, first difference, seasonally adjusted; 2020=100). Source: Bank for International Settlements (BIS).
- Selic: Brazil’s policy interest rate, last observation of the month (BCB series 432). Source: BCB.
- Global Supply Chain Pressure Index (GSCPI), United States: monthly index. Source: Federal Reserve Bank of New York.
- Global Supply Chain Pressure Index (GSCPI), Brazil: monthly index. Source: BCB.

The MCT estimation and the TVP-VAR-DY connectedness analysis in Section 2.6.1 use the full sample, August 1999 to May 2026. The local projection exercise in Section 2.6.1, however, is estimated on a shorter sample starting in January 2003, since the IBC-Br control is available only from that date onward; because the REER enters the local projection specification in first differences, the effective sample begins one month later, in February 2003, and runs through April 2026 ($T = 279$). To keep the system balanced, all series in the local projection exercise, including the Selic and the MCT trends, are restricted to this common window. Appendix Table A1 reports descriptive statistics and Appendix Table A2 reports unit root and structural break tests (ADF, PP, KPSS, and Zivot, and Andrews (1992)) for these variables. The Selic and the permanent trend of Food Away From Home show evidence of a unit root under the ADF and KPSS tests, but the Zivot, and Andrews (1992) test rejects the unit-root null once a single endogenous break is allowed for, indicating a level shift rather than a stochastic trend; this motivates retaining the Selic in levels in Equations (2.21)–(2.22).

The sample totals 322 monthly observations. The expenditure shares of each group in the IPCA basket were reconstructed bottom-up from sub-item codes available in the IBGE Automatic Recovery System (SIDRA), following the criteria adopted by the BCB for the construction of the EX1 exclusion core, and excluding administered-price sub-items re-normalized within each group. This procedure ensures consistency across the three Household Budget Survey weighting structures in force during the sample: POF 2002–2003 until December 2011, POF 2008–2009 from January 2012 to December 2019, and POF 2017–2018 from January 2020 onward.

Table 2.1 presents the descriptive statistics for all system variables. The monthly inflation average for Food at Home (0.62%) matches the headline IPCA average (0.51%) only loosely, exceeding it by roughly eleven basis points, a pattern accompanied by markedly higher volatility (a standard deviation of 1.07% versus 0.39%) and a sharper maximum peak (6.78% versus 3.04%).

Table 2.1 – Descriptive Statistics and Expenditure Weights (monthly inflation, %)

Series	Descriptive Statistics					Weight (%)			
	Mean	Median	Max	Min	Std. Dev.	Aug/1999 –Dec/2011	Jan/2012 –Dec/2019	Jan/2020 –May/2026	Full sample
<i>A. Food</i>									
Food and Beverages	0.62	0.58	5.93	−1.07	0.81	23	25	21	23
Food at Home	0.62	0.57	6.78	−1.84	1.07	18	16	15	17
Food Away from Home	0.61	0.59	2.85	−0.30	0.39	5	9	6	7
<i>B. Non-food Groups</i>									
Housing	0.52	0.46	5.29	−3.08	0.78	14	15	15	15
Household Items	0.29	0.27	2.88	−1.37	0.54	5	4	4	4
Clothing	0.46	0.49	2.11	−1.44	0.59	6	6	5	6
Transportation	0.46	0.35	4.68	−4.51	0.96	21	19	21	20
Health & Personal Care	0.51	0.44	2.74	−0.71	0.42	11	12	13	12
Personal Expenses	0.54	0.49	3.55	−0.31	0.42	9	11	10	10
Education	0.56	0.12	6.70	−3.47	1.35	6	5	6	6
Communication	0.29	0.07	9.31	−2.08	1.04	5	4	5	5
<i>C. Headline and Core Inflation</i>									
IPCA – Headline	0.51	0.46	3.04	−0.68	0.39	100	100	100	100
Core Inflation – EX1	–	–	–	–	–	82	83	82	82

Source: IBGE/SIDRA, authors' calculations.

Notes: Sample August 1999 to May 2026 ($T = 322$ months). Weights are period-average EX1 expenditure shares reconstructed bottom-up from IBGE/SIDRA sub-item codes following BCB EX1 criteria, excluding administered-price sub-items and re-normalized within each group. POF 2002–2003 in force until Dec/2011; POF 2008–2009 from Jan/2012 to Dec/2019; POF 2017–2018 from Jan/2020 onward.

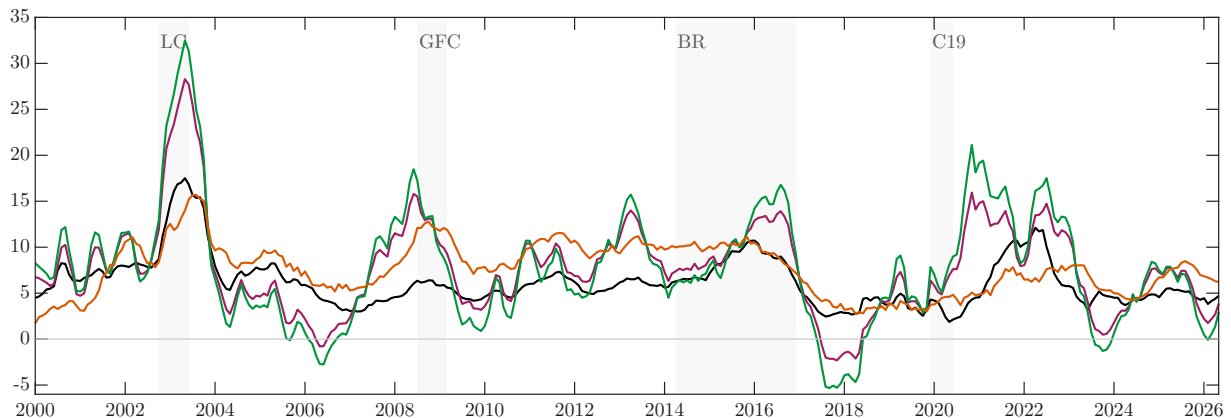
Food Away From Home displays a similar average (0.61%) but a much more contained dispersion (0.39%), close to the headline series. Among the non-food groups, Education and Communication record the highest volatility (standard deviations of 1.35% and 1.04%, respectively), reflecting administered-price adjustment cycles, while Health and Personal Care and Personal Expenses remain closest to the headline benchmark.

Figure 2.1 uncovers the underlying temporal patterns and helps evaluate the historical dynamics of inflation across the food subcomponents over time, by tracking the 12-month accumulated inflation for the headline IPCA, Food and Beverages, Food at Home, and Food Away From Home. The shaded areas denote recessions dated by the Brazilian Economic Cycle Dating Committee (CODACE/FGV, 2023). The historical trajectories reveal distinct cyclical behaviors and structural heterogeneity that motivate the disaggregated analysis. During the Lula Crisis of 2002–2003, both food subcomponents surged sharply: Food at Home reached 32.49% in May 2003, driven by the exchange rate depreciation and an agricultural supply shock, while Food Away From Home reached 15.68% in August 2003, a smaller but still pronounced increase lagging Food at Home by three months and reflecting cost-push transmission through labor and service inputs. At the Global Financial Crisis episode, Food at Home peaked at 18.48% in June 2008 while Food Away From Home reached 12.78% in October 2008, with a four-month lag.

During the Great Brazilian Recession, Food Away From Home peaked earlier, at 11.10% in November 2015, while Food at Home peaked later and higher, at 16.78% in August 2016 –

the only episode in the sample in which Food Away From Home leads rather than lags Food at Home, consistent with a demand-driven shock that first reached consumer services before feeding into food commodity costs. The pandemic episode exhibits the greatest asymmetry: Food at Home surged to 21.13% in November 2020, while Food Away From Home reached only 8.04% in February 2023, a twenty-seven-month lag that reflects the delayed propagation of domestic food cost pressures through the food service labor market. This heterogeneity highlights the differentiated transmission of aggregate shocks across food subcomponents, amplifying measurement challenges for core inflation through different supply and demand channels.

Figure 2.1 – IPCA Inflation Dynamics Across Food (12-month cumulative %)



— Headline IPCA — Food and Beverages — Food at Home — Food Away From Home
Source: IBGE/SIDRA, authors' calculations.

Note: 12-month accumulated inflation rates for the headline IPCA, Food and Beverages, Food at Home, and Food Away From Home. Shaded areas denote recessions dated by CODACE (CODACE/FGV, 2023). LC = Lula Crisis 2002–2003; GFC = Global Financial Crisis; BR = Great Brazilian Recession; C19 = COVID-19 pandemic.

Unlike the original MCT application at the Federal Reserve Bank of New York, whose model is estimated using all seventeen PCE sectors, including food and energy, but excludes these non-core sectors only at the stage of aggregating the final trend measure (Almuzara, and Sbordon, 2022), this paper applies the same aggregation logic in reverse. The model is estimated using all ten IPCA groups, including Food at Home and Food Away From Home, and the sectoral weights used in the final aggregation step, analogous to the Fed's `share_xfe`, assign zero weight to Food at Home, the component of interest for the food decomposition, while retaining Food Away From Home, whose service-linked cost structure resembles the Fed's treatment of "Food services and accommodations" as a core component. The empirical model applied to this disaggregated dataset is the Multivariate Core Trend (MCT), which extends the Multivariate Unobserved Components Stochastic Volatility with Outliers (MUCSVO) of Stock, and Watson (2016) by allowing the transitory component to follow a moving-average process instead of white noise, following Almuzara, and Sbordon (2022) and Almuzara, and Sbordon (2024). This matters for Food at Home and Food Away From Home, whose distinct cost structures should produce different transitory-shock persistence profiles, which a white-noise specification would fail to capture. Section 2.4 presents the full derivation of the model.

2.4 Methodology

To characterize the persistence of Brazilian food inflation, this chapter estimates the Multivariate Core Trend (MCT), a state-space model introduced by Almuzara, and Sbordon

(2022) and formally described in Almuzara, and Sbordone (2024). To our knowledge, this is the first time the MCT has been estimated on Brazilian price data. The model belongs to a family of unobserved-components specifications with stochastic volatility that originates with Stock, and Watson (2007), who proposed separating an inflation series into a persistent component and a noise component whose relative variances are allowed to shift over time. Stock, and Watson (2016) extended this idea along two further paths. First, they built a single-series version, the Unobserved Components Stochastic Volatility Outlier-adjusted model (UCSVO), which also flags and downweights unusually large observations in the noise term. Second, they generalized the specification to many series estimated jointly, the Multivariate Unobserved Components Stochastic Volatility with Outliers model (MUCSVO), in which a factor common to all sectors and a set of sector-specific factors jointly account for both the trend and the noise, with each sector's sensitivity to the common factor allowed to drift over time. The MCT is an extension of the MUCSVO, not of the univariate UCSVO: it takes the multivariate common-factor structure of the MUCSVO as its starting point and replaces the white-noise assumption for the transitory component with a finite moving-average process, so that a shock recorded in one month can leave a footprint over several subsequent months instead of vanishing immediately. This matters because monthly, rather than quarterly or annual, price data typically display shocks that do not reverse within a single period. The remainder of this section presents the model step by step, following the exposition in Almuzara, and Sbordone (2024).

Consider first the single-series case studied by Stock, and Watson (2007). Aggregate inflation in period t is written as the sum of a persistent, trend-like term and a mean-zero transitory term:

$$\pi_t = \tau_t + \varepsilon_t \quad (2.1)$$

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t} \eta_{\Delta\tau,t} \quad (2.2)$$

$$\varepsilon_t = \sigma_{\varepsilon,t} \eta_{\varepsilon,t} \quad (2.3)$$

$$\Delta \ln \sigma_{\Delta\tau,t}^2 = \gamma_{\Delta\tau} \nu_{\Delta\tau,t} \quad (2.4)$$

$$\Delta \ln \sigma_{\varepsilon,t}^2 = \gamma_{\varepsilon} \nu_{\varepsilon,t} \quad (2.5)$$

All shock terms are mutually and serially independent standard normal random variables, following the stochastic-volatility specification of Kim, Shephard, and Chib (1998). Stock, and Watson (2016) augment this univariate setup with a mechanism that identifies and downweights unusually large innovations in the transitory term, yielding the UCSVO described above. Stock, and Watson (2016) then generalize the UCSVO to a system of N sectors estimated jointly, yielding the MUCSVO, the specification adopted in what follows. For sector i in period t , inflation is written as:

$$\pi_{it} = \alpha_{\tau,it} \bar{\tau}_{ct} + \bar{\tau}_{it} + \alpha_{\varepsilon,it} \bar{\varepsilon}_{ct} + \bar{\varepsilon}_{it} \quad (2.6)$$

where the common trend $\bar{\tau}_{ct}$ reaches every sector through the sector-specific sensitivity $\alpha_{\tau,it}$, while $\bar{\tau}_{it}$ captures trend movements idiosyncratic to sector i . The same logic applies to the transitory block, $\bar{\varepsilon}_{ct}$ and $\bar{\varepsilon}_{it}$. Both the common and the sector-specific trends follow random walks whose innovation variances change over time:

$$\bar{\tau}_{ct} = \bar{\tau}_{c,t-1} + \sigma_{\Delta\tau,ct} \eta_{\Delta\tau,ct} \quad (2.7)$$

$$\bar{\tau}_{it} = \bar{\tau}_{i,t-1} + \sigma_{\Delta\tau,it} \eta_{\Delta\tau,it} \quad (2.8)$$

$$\Delta \ln \sigma_{\Delta\tau,ct}^2 = \gamma_{\Delta\tau,c} \nu_{\Delta\tau,ct} \quad (2.9)$$

$$\Delta \ln \sigma_{\Delta\tau,it}^2 = \gamma_{\Delta\tau,i} \nu_{\Delta\tau,it} \quad (2.10)$$

On the transitory side, the same outlier-adjustment device used in the univariate UCSVO

is applied separately to the common and the sector-specific components:

$$\bar{\varepsilon}_{ct} = \sigma_{\varepsilon,ct} o_{\varepsilon,ct} \eta_{\varepsilon,ct} \quad (2.11)$$

$$\bar{\varepsilon}_{it} = \sigma_{\varepsilon,it} o_{\varepsilon,it} \eta_{\varepsilon,it} \quad (2.12)$$

$$\Delta \ln \sigma_{\varepsilon,ct}^2 = \gamma_{\varepsilon,c} \nu_{\varepsilon,ct} \quad (2.13)$$

$$\Delta \ln \sigma_{\varepsilon,it}^2 = \gamma_{\varepsilon,i} \nu_{\varepsilon,it} \quad (2.14)$$

the indicators $o_{\varepsilon,ct}$ and $o_{\varepsilon,it}$ equal one with probability p_c and p_i , respectively, and are otherwise drawn from a uniform distribution on $[1, \bar{s}]$, so that an outlier inflates the scale of the corresponding innovation for a single period without permanently shifting the volatility path. Unlike the fixed sensitivities of a standard common-factor model, the loadings on the common trend and the common transitory shock are themselves allowed to evolve, following independent random walks, completing the MUCSVO specification of Stock, and Watson (2016):

$$\Delta \alpha_{\tau,it} = \lambda_{\tau,i} \nu_{\tau,it} \quad (2.15)$$

$$\Delta \alpha_{\varepsilon,it} = \lambda_{\varepsilon,i} \nu_{\varepsilon,it} \quad (2.16)$$

The MCT of Almuzara, and Sbordone (2022) and Almuzara, and Sbordone (2024) extends this MUCSVO specification on a single point, concerning the transitory block alone. Rather than treating $\bar{\varepsilon}_{ct}$ and $\bar{\varepsilon}_{it}$ as serially uncorrelated, as in the MUCSVO, the MCT lets each follow a finite moving-average process of order p :

$$\bar{\varepsilon}_{ct} = (1 + \theta_{c1}L + \dots + \theta_{cp}L^p) \sigma_{\varepsilon,ct} o_{\varepsilon,ct} \eta_{\varepsilon,ct} \quad (2.17)$$

$$\bar{\varepsilon}_{it} = (1 + \theta_{i1}L + \dots + \theta_{ip}L^p) \sigma_{\varepsilon,it} o_{\varepsilon,it} \eta_{\varepsilon,it} \quad (2.18)$$

where L denotes the lag operator. With monthly data, a supply disruption or a one-off price adjustment often takes more than a single period to fully reverse. The moving-average terms $\theta_{c1}, \dots, \theta_{cp}$, and their sector-specific counterparts, let the model absorb that partial persistence within the transitory block, rather than attributing it to the permanent trend, which is precisely what distinguishes the MCT from the MUCSVO on which it builds.

Aggregating across sectors with the average expenditure share $\tilde{s}_{it} = (s_{i,t-1} + s_{it})/2$ delivers the object of interest, the trend component of aggregate inflation, which can itself be split into the portion attributable to the common factor and the portion attributable to sector-specific dynamics:

$$\hat{\tau}_t = \sum_{i=1}^N \tilde{s}_{it} \tau_{it} = \underbrace{\sum_{i=1}^N \tilde{s}_{it} \alpha_{\tau,it} \bar{\tau}_{ct}}_{\text{common component}} + \underbrace{\sum_{i=1}^N \tilde{s}_{it} \bar{\tau}_{it}}_{\text{sector-specific component}} \quad (2.19)$$

The full system given by Equations (2.6)–(2.19) is estimated via conditional Gibbs Sampling, cycling through the parameter blocks in turn within each sweep of the chain. As already noted, the MCT extends the MUCSVO of Stock, and Watson (2016) on a single point: rather than treating the transitory component as serially uncorrelated, it lets it follow a finite moving-average process, so that a shock can leave a footprint over several months instead of dissipating at once. The outlier mechanism itself, by contrast, is inherited unchanged from the univariate UCSVO and the MUCSVO: the indicators $o_{\varepsilon,ct}$ and $o_{\varepsilon,it}$ equal one with probability p_c and p_i , and are otherwise drawn from a uniform distribution on $[1, \bar{s}]$, inflating the scale of the corresponding innovation for a single period without permanently shifting the volatility path. The moving-average coefficients receive a Normal prior with precision increasing in the

square of the lag order, $\theta_{ij} \sim N(0, 1/(0.1j^2))$, with invertibility imposed at every draw. The time-varying loadings, $\alpha_{\tau,it}$ and $\alpha_{\varepsilon,it}$, follow a random walk whose innovation variance λ is governed by an Inverse-Gamma prior with 12 degrees of freedom. Stochastic volatilities are approximated by a ten-component Gaussian mixture and sampled via the block sampler of Omori et al. (2007), with the volatility-of-volatility parameter γ governed by a considerably tighter Inverse-Gamma prior, 60 degrees of freedom. The probability of the normal state, p_c and p_i , follows Beta(117.5, 2.5), a calibration equivalent to an outlier expected roughly once every four years, following Stock, and Watson (2016).

Seasonality is not removed from the series prior to estimation; instead, it is handled endogenously within the model itself. A deterministic monthly-dummy term, $\sum_{m=1}^{12} D_{mt} \delta_{im}$, enters the measurement equation directly, with $\delta_{im} \sim N(0, \kappa_{\delta,i}^2)$ acting as a sector-specific hierarchical prior. The values of $\kappa_{\delta,i}^2$ are fixed rather than estimated, calibrated to the historical magnitude of calendar-driven price adjustments in each sector: 0.15 for most groups, 10.0 for Education, given the size of February tuition resets, and 1.0 for Communication, given the July tariff cycle. This lets a recurring calendar pattern compete directly with the outlier indicator for the same variation, rather than being misclassified as an anomaly.

2.5 Empirical Results

Figure 2.2 presents the Multivariate Core Trend (MCT) results disaggregated into four panels. Panel (a) depicts the twelve-month accumulated trend of the headline IPCA alongside the trends for Food and Beverages, Food at Home, and Food Away from Home. Panels (b) and (c) report the permanent and transitory components of the stochastic volatility, respectively, while Panel (d) displays the posterior outlier probabilities.

By applying the Multivariate Core Trend (MCT) state-space framework to the Extended National Consumer Price Index (IPCA), we isolate persistent underlying inflation trends from transitory volatility, which can be analyzed through selected historical milestones (Panel a). The 2003 peak marked the following trend inflation rates: Headline (17.50%) and Food at Home (24.83%), characterized by the aforementioned election-induced uncertainty which led to exchange rate crises, currency pass-through, and expectation de-anchoring. The 2008 peak marked a 6.04% Headline trend inflation, with Food at Home reaching 14.25% due to the global commodity boom. Following a period of stabilization, the New Macroeconomic Matrix crisis and subsequent deep recession led to the 2017 trough, where Headline trend inflation dropped to 2.70% and Food at Home fell to -3.06%. Finally, the 2021 pandemic peak drove trend inflation to 8.97% for the Headline IPCA and 14.80% for Food at Home.

The empirical findings reveal that Brazilian food inflation is characterized by a dual-regime structural persistence. While Food at Home (FAH) operates as a high-frequency, high-amplitude conduit for global supply chain and climate cost-push shocks, Food Away from Home (FAFH) functions as a low-frequency, highly inertial anchor rooted in service sector indexation. To characterize the transmission dynamics between these two regimes, we estimate the Sample Cross-Correlation Function (CCF) between the twelve-month accumulated trend components of Food at Home (FAH_t) and Food Away from Home ($FAFH_t$). The results point to a fast-acting, rather than a delayed, transmission mechanism. The contemporaneous correlation (at $k = 0$) is already substantial ($r = 0.56$), rejecting the notion of a fully delayed pass-through. The cross-correlation function peaks shortly thereafter, between lags $k = 1$ and $k = 3$ ($r = 0.62$ at the maximum), and then decays steadily as the lag lengthens, falling below $r = 0.15$ by $k = 18$ – 22 . This pattern indicates that cost-push shocks originating in the retail food segment propagate into the service-dependent food segment within a few months rather than over a one-and-a-half to two-year horizon; what distinguishes Food Away from Home is not a delayed

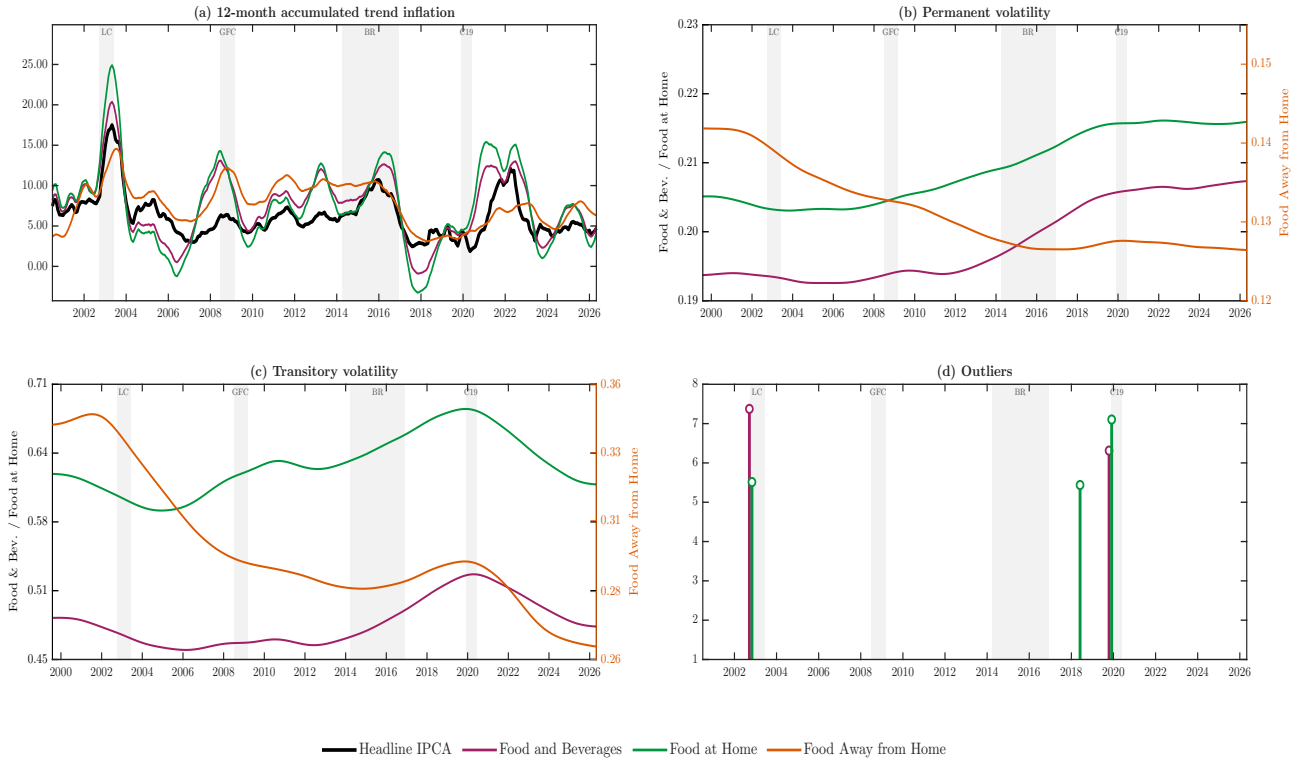
reception of the shock, but the greater persistence of the shock once it is absorbed, consistent with the low transitory and comparatively higher permanent volatility documented for this subcomponent in Panels (b) and (c).

The clear heterogeneity in trend inflation shown in Panel (a) is a result of the behavior of the Permanent Volatility, given by Panel (b). The permanent component of stochastic volatility isolates time-varying, non-mean-reverting variance, mapping how deeply structural shocks are embedded into the long-term baseline of inflation, and how they impact inflation. The empirical results reveal a profound structural divergence, and subsequent convergence, between Food at Home (FAH) and Food Away from Home (FAFH). Initiating the sample at an elevated baseline of around 0.21, Food at Home permanent volatility experienced a minor currency-backed contraction until 2006, where it stabilized at 0.20. From 2006 onward, however, the series entered an upward trajectory, accelerating progressively through the 2010s to reach its historical plateau of 0.215 during the COVID-19 pandemic, remaining fixed at this high-uncertainty equilibrium through 2025. This permanent upward break reflects the deep integration of Brazilian agriculture into global futures markets and an escalating regime of structural climate risks.

The permanent volatility of Food Away from Home, in contrast, displays the exact opposite behavior. Starting at 0.135, its permanent volatility underwent a prolonged, sharp contraction until 2017, reaching a structural trough of 0.125. This "Great Volatility Moderation" reflects the steady expansion of domestic real wages and formal employment, allowing firms to smooth pricing strategies. Post-2017, FAFH staged a mild reversal back to its historical baseline as restaurants and bars were forced to structurally recompose compressed profit margins. The permanent volatility of the Aggregate Food and Beverages as a whole synthesizes this tension, starting at 0.19 in 2000, pausing briefly at 0.195 in 2010–2011, and accelerating sharply to hit 0.21 during the pandemic. Crucially, the volatility gap between aggregate food and grocery items progressively closed over the sample. This structural convergence proves that global supply-side shocks overrode domestic service-stabilization forces, locking long-term food uncertainty at a structurally higher baseline in the mid-2020s.

Unlike its permanent counterpart, transitory stochastic volatility isolates high-frequency, short-lived innovations that are strictly mean-reverting. The empirical estimates shown in Panel (c) map distinct cyclical waves that fully unwind over the business cycle. Reflecting menu costs, and wage rigidities inherent in the services sector, Food Away from Home displays the smallest transitory volatility magnitudes in the entire system, starting at 0.34, steadily compressing to a historical minimum of 0.28 in 2015, and dropping further to 0.26 by 2025. In contrast, grocery items (Food at Home) act as the primary conductor of immediate price shocks, opening the sample at an extremely volatile baseline of 0.63. Following a macro-stabilization drop to 0.60 in 2006, the transitory volatility of Food at Home entered a highly volatile, oscillating upward phase through 2011, as a result of the international commodity boom. This high-frequency uncertainty surged violently during the pandemic, hitting a historical peak of 0.68, as lockdown supply disruptions locked retail pricing into chaos.

Figure 2.2 – MCT of Food Inflation: Trend, Volatility, and Outlier Probability



Source: Authors' calculations. Note: Panel (a): twelve-month accumulated trend (%). Panel (b): permanent volatility (posterior median of the standard deviation of the trend increment). Panel (c): transitory volatility (posterior median of the standard deviation of the transitory component). Panel (d): posterior outlier probability. Shaded areas denote recessions dated by (CODACE/FGV, 2023).

The Food and Beverages aggregate index perfectly captures this cyclical wave, descending from 0.48 to 0.45 in 2006, holding stable until the onset of the 2014 domestic stagflationary crisis, and climbing steadily to 0.53 in 2020. Proving the robust mean-reverting nature of this component, both the Aggregate Food index and the Food at Home component fell symmetrically back to their exact initial values by 2025, demonstrating that once the pandemic-era logistical bottlenecks dissolved, high-frequency excess variance was completely drained from the system.

The posterior outlier probabilities isolate deterministic, maximum-magnitude innovations that lack time-series persistence, preventing them from biasing the volatility trends. The model identifies a structural inversion of shock intensities between the 2002–2003 crisis and more recent supply disruptions. During the 2002 presidential transition and exchange rate crisis, the posterior outlier probability for the Aggregate Food index peaked at 0.90, while the localized Food at Home component was contained at around 0.60. The data confirms that the 2002 shock was a widespread macroeconomic inflationary pressure that initially impacted logistics and distribution networks, while the retail sector temporarily delayed the full pass-through to consumers. In mid-2018 there is a unique, idiosyncratic supply shock exclusive to Food at Home, reaching 0.60. This maps the microstructural paralysis of the national truck drivers’ strike, which affected the supply of perishable grocery stocks. During the COVID-19 shock, the outlier intensities inverted completely. Food at Home increased to its historical maximum of 0.85, whereas the Aggregate index stayed at 0.75. Because physical lockdowns closed the restaurant sector, FAFH pricing power dropped to zero. This service paralysis acted as a structural dampener, absorbing the aggregate shock, even as supermarkets experienced an unprecedented, concurrent positive demand wave and global supply chain collapse.

Therefore, the long-term tracking enabled by the MCT reveals a distinct behavioral tax-

onomy across the components of the Brazilian inflation basket. The Headline IPCA presents moderate volatility and a balanced inertial response; driven primarily by common macro shocks, it shows high monetary policy elasticity, making it highly responsive to interest rate transmission. Conversely, the Food at Home component is characterized by extreme volatility and a low or short-lived inertial response. Its primary driving factors are global commodities and climate conditions, resulting in low monetary policy elasticity since it is dominated by international prices and input costs. Finally, Food Away from Home exhibits low volatility but an extremely high inertial response. It is heavily driven by service indexation and wages, displaying moderate monetary policy elasticity as it remains protected by indexation lags.

To map the underlying transmission mechanism, the Multivariate Core Trend (MCT) decomposes the structural headline inflation trend into orthogonal Common (systemic) and Sector-Specific (idiosyncratic) components. The economic diagnosis across key historical epochs clearly demonstrates the dual-regime dynamics previously discussed. The Food at Home (FH) sector is highly sensitive to exchange rate fluctuations and reacts more intensely to global macroeconomic shocks (Common column). On the other hand, the Food Away from Home (FA) sector exhibits strong demand sensitivity, operating with greater inertia as it remains intrinsically tied to domestic service and labor cycles.

Table 2.2 quantifies this decomposition for eight historical episodes selected for their macroeconomic significance, reporting the annual total MCT alongside its four structural components (FH Sector, FH Common, FA Sector, FA Common), the contemporaneous Global Supply Chain Pressure Index for the United States and Brazil, and the prevailing Selic policy stance. This year-by-year breakdown makes it possible to attribute each inflationary episode to either a domestic sector-specific shock, a common macroeconomic factor, or an imported supply chain disturbance, and to assess whether the observed monetary policy response was proportionate to the underlying source of the shock.

Table 2.2 – Multivariate Core Trend (MCT) Structural Decomposition and Policy Response

Year	Total MCT	FH Sector	FH Common	FA Sector	FA Common	GSCPI USA	GSCPI Brazil	Monetary Policy
2003	4.23	-0.15	0.31	0.17	0.09	-0.28	-0.50*	Tightening
2005	1.46	-0.41	-0.07	-0.02	-0.01	-0.56	-0.65*	Tightening
2011	0.33	0.03	-0.07	0.24	-0.01	0.32	-0.43	Easing
2015	1.25	0.16	0.22	0.16	0.04	-0.51	-0.35	Tightening
2017	-0.77	-0.39	-0.40	-0.24	-0.07	0.30	-0.65	Easing
2020	-3.09	0.43	0.08	-0.21	-0.00	1.64	1.11	Easing
2022	2.81	-0.01	0.28	-0.03	0.02	2.20	2.67	Tightening
2026	-0.83	0.13	0.10	-0.10	-0.01	1.05	0.55*	Easing

Source: Authors' calculations. Notes: Total MCT, FH/FA Sector and Common are annual averages of the 12-month accumulated series, demeaned (2000–2026). GSCPI USA/Brazil: annual averages, not demeaned. * Years outside the Apr/2006–Aug/2022 GSCPI Brazil coverage window (see Section 2.3) use the maritime freight proxy. 2026 is a partial year (through May).

The year 2003 marked a peak in total MCT at 4.23%, characterized by a regime where monetary policy proved ineffective. The shock was essentially driven by domestic monetary unanchoring and severe exchange rate pass-through into commodity and contract prices, overriding the negative pressures from global supply chains (GSCPI USA at -0.28; GSCPI Brazil at -0.50). On the other hand, the year 2005 was marked by decreasing prices, bringing the total MCT down to 1.46%. Although common factors collapsed due to central bank credibility, global commodity pressures persisted despite negative global supply chain indicators (GSCPI USA at -0.56; GSCPI Brazil at -0.65), isolated by the negative sector-specific shock in FH (-0.41%).

By 2011, the trend inflation dynamics (MCT of 0.33%) and monetary policy achieved moderate effectiveness by cooling aggregate demand, which countered a moderate global supply chain disruption (GSCPI USA at 0.32). While domestic logistics remained insulated (GSCPI Brazil at -0.43), the primary inflationary driver was the demand-pull channel captured by the Sector FA component (0.24%), which absorbed the domestic overheating through its high indexation to wages and services. This dynamic contrasts sharply with 2015, where monetary policy was highly ineffective. The total MCT rose to 1.25%, driven largely by domestic currency problems, fuel shocks, and administered energy tariffs that decoupled from the still-mildly deflationary global supply conditions (GSCPI USA at -0.51; GSCPI Brazil at -0.35).

The structural decomposition for 2017 highlights that BCB policy played a passive, neutral role. While the 2014–2016 recession left deep macroeconomic scars, with a severely negative output gap and high unemployment suppressing domestic demand, the exceptional domestic agricultural performance triggered a sizable supply-side deflationary shock (GSCPI Brazil at -0.65). This local bumper crop largely insulated consumer prices from mild international logistical pressures (GSCPI USA at 0.30), driving Sector FH to -0.39% and Common FH to -0.40%, and anchoring the inertial service components (Sector FA at -0.24%; Common FA at -0.07%), culminating in a total MCT of -0.77%. Finally, the recent shocks illustrate two extremes of global integration. The onset of the 2020 pandemic challenged monetary policy actions. The aggregate demand shutdown was overwhelmed by systemic global supply pressures (GSCPI USA at 1.64; GSCPI Brazil at 1.11), despite a total MCT of -3.09%. This setup evolved into the 2022 total MCT of 2.81%, a typical supply-side crisis, driven by the geopolitical cost-push episode triggered by the outbreak of the war in Ukraine (GSCPI USA at 2.20; GSCPI Brazil at 2.67) and the subsequent global supply chain crisis.

Figure 2.3 presents the Layers of Inflation Persistence decomposition, inspired by Almuzara, Jarocinski, and Sbordon (2023), adapted to the Brazilian food sector. The figure decomposes the twelve-month accumulated trend change into common and sector-specific contributions shown in Table 2.2, tracing how the sources of food inflation persistence shifted across the major macroeconomic episodes discussed above.

Together, the MCT results support the central thesis: food inflation in Brazil is not a homogeneous phenomenon and the uniform treatment of food shocks as transitory in monetary policy is empirically incorrect for the domestic food subcomponent. Food at Home exhibits growing persistence in the permanent component and produces high-probability outliers in the major supply shock episodes, implying that shocks in this subcomponent warrant careful monitoring by the central bank when they extend beyond two or three months. Food Away From Home absorbs most of its shocks in the transitory component and rarely produces outliers of significant magnitude, making the transitory treatment relatively more defensible for this subcomponent.

Figure 2.3 – Layers of Food Inflation Persistence: Common vs. Sector-Specific Decomposition



Source: Authors' calculations. Note: Annual bar charts showing the decomposition of the twelve-month accumulated trend into common and sector-specific components for Food at Home, Food Away From Home, and the IPCA. Panel (d) overlays the Global Supply Chain Pressure Index (GSCPI) on the right axis. Shaded areas denote recessions dated by (CODACE/FGV, 2023).

2.6 The BCB Reaction to Food Inflation Volatility

2.6.1 The Selic Interest Rate and Volatility Spillovers

We next examine how the central bank reacts to permanent and transitory volatility in food inflation, using a time-varying connectedness framework applied to the volatilities extracted by the MCT. Let y_t denote the vector of permanent or transitory volatilities for the relevant IPCA groups at time t . The connectedness framework is built on a Time-Varying Parameter Vector Autoregression:

$$y_t = c_t + B_t y_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, \Sigma_t) \quad (2.20)$$

where the intercept c_t and the coefficient matrix B_t are time-varying, capturing how the transmission of volatility across groups evolves over the sample, following Koop, and Korobilis (2013), Antonakakis, Chatziantoniou, and Gabauer (2020), and Gabauer, and Gupta (2018). As a robustness check, we re-estimate the system replacing the Selic level with its first difference; the disaggregated system is materially robust to this respecification while the aggregate system is not, so we place the analytical weight of this section on the disaggregated system. The full methodological framework, diagnostic tests, and robustness results are omitted here for space but remain available upon request.

The results show that the Selic transmits more volatility to the rest of the system than it receives (a positive net position in Table 2.3, Panels A and C: +15.0% in the aggregate system and +20.6% in the disaggregated system), and that this transmission relationship strengthens considerably once food is split into its at-home and away-from-home components (the overall degree of interconnection rises from 18.44% to 32.51%). Within the disaggregated system (Panel C), the permanent volatility of food away from home is the component that most consistently

absorbs volatility originating elsewhere (a negative net position of -23.9%), particularly from its own transitory component, while the Selic receives more of its incoming volatility from the permanent component of food away from home (10.2%) than from food at home (6.3%), consistent with monetary policy tracking the more persistent, service-linked price dynamics.

Table 2.3 – Volatility Connectedness and Average NET Spillover by CODACE Episode (%)

Panel A: Aggregate, Static Connectedness							Panel B: Aggregate, Average NET by CODACE Episode						
From/To	P.F	T.F	P.FA	T.FA	FROM	Selic	Period	P.F	T.F	P.FA	T.FA	Selic	
Perm.Food	73.9	14.4			26.1	11.7	Full sample	−15.5	+0.4			+15.0	
Trans.Food	7.5	80.0			20.0	12.5	Pre-crisis	−23.0	−0.6			+23.6	
Selic	3.1	6.1			9.2	90.8	LC (Oct/02–Jun/03)	−39.1	−0.7			+39.8	
TO	10.6	20.5				24.2	GFC (Jul/08–Mar/09)	−21.1	+2.7			+18.4	
NET	−15.5	+0.4				+15.0	BR (Apr/14–Dec/16)	−10.4	−3.0			+13.4	
TCI	18.44%						C19 (Dec/19–Jun/20)	−4.4	+0.4			+3.9	
							Post-COVID	−20.3	+6.1			+14.2	
Panel C: Disaggregated, Static Connectedness							Panel D: Disaggregated, Average NET by CODACE Episode						
From/To	P.FH	T.FH	P.FA	T.FA	FROM	Selic	Period	P.FH	T.FH	P.FA	T.FA	Selic	
Perm.FH	58.6	18.2	10.5	6.3	41.4	6.3	Full sample	−24.8	+18.6	−23.9	+9.5	+20.6	
Trans.FH	3.2	74.0	3.5	7.8	26.0	11.5	Pre-crisis	−66.2	+54.2	−27.5	+23.4	+16.0	
Perm.FA	8.1	9.9	48.8	23.0	51.2	10.2	LC (Oct/02–Jun/03)	−78.7	+67.2	−26.1	−8.5	+46.0	
Trans.FA	3.1	10.9	10.9	69.2	30.8	5.8	GFC (Jul/08–Mar/09)	−7.7	+4.3	−27.9	+22.7	+8.6	
Selic	2.2	5.5	2.4	3.3	13.3	86.7	BR (Apr/14–Dec/16)	−27.5	+20.8	−16.7	+5.8	+17.6	
TO	16.6	44.5	27.3	40.3		33.9	C19 (Dec/19–Jun/20)	−34.8	+28.4	−0.4	+12.0	−5.1	
NET	−24.8	+18.6	−23.9	+9.5		+20.6	Post-COVID	+4.4	+5.0	−32.7	−1.8	+25.1	
TCI	32.51%												

Notes: Panels A–B report the aggregate specification (3 variables: Perm.Food, Trans.Food, Selic); Panels C–D report the disaggregated specification (5 variables: Perm.FH, Trans.FH, Perm.FA, Trans.FA, Selic). Connectedness via GFEVD (Pesaran, and Shin, 1998); TVP-VAR with $\kappa_1 = 0.99$, $\kappa_2 = 0.96$, $H = 12$ (Antonakakis, Chatziantoniou, and Gabauer, 2020). P. = Perm. = permanent volatility ($\hat{\sigma}_{\Delta\tau}$); T. = Trans. = transitory volatility ($\hat{\sigma}_{\varepsilon}$), both from the MCT model. FH = Food at Home; FA = Food Away from Home. Selic: BCB series 432, last observation of the month. NET = TO – FROM (%); positive: net transmitter. Full sample: full-period time-series average. LC = Lula Crisis (Oct/2002–Jun/2003); GFC = Global Financial Crisis (Jul/2008–Mar/2009); BR = Brazilian Recession (Apr/2014–Dec/2016); C19 = COVID-19 pandemic (Dec/2019–Jun/2020). Sample: Aug/1999–May/2026.

Splitting the sample by CODACE cyclical episodes (Panels B and D) reveals a shift concentrated in the disaggregated system. The Selic’s capacity to transmit stability to the rest of the system weakens over the sample in the aggregate specification (Panel B), from $+39.8\%$ during the Lula Crisis to $+3.9\%$ during COVID-19, before recovering to $+14.2\%$ Post-COVID, though this specification is sensitive to how the interest rate is measured. More robustly, food away from home’s permanent volatility (Panel D) continues to absorb volatility from the rest of the system in every episode, intensifying from -27.5% in the pre-crisis period to -32.7% Post-COVID, its most negative value in the sample, while food at home’s permanent volatility, historically an absorber like food away from home, becomes for the first time a source of volatility for the rest of the system in the same period ($+4.4\%$), the only episode in which it does so. This shift originates in the component most exposed to agricultural commodity shocks, pointing monetary policy attention toward the persistence of commodity-linked shocks rather than services inertia.

2.6.2 The Selic Interest Rate and Local Projection Impulse Responses

To complement the connectedness analysis, we estimate local projections (Jordà, 2005) in two directions. In the direct exercise, the Selic rate is the shock and the MCT permanent trend of each food subcomponent is the dependent variable; a negative response indicates that

contractionary monetary policy compresses the permanent component of food inflation. In the inverse exercise, each food trend is the shock and the Selic is the dependent variable; a positive response captures the reaction function of the Copom, showing that the central bank tightens in response to rising permanent food inflation.

The direct specification at horizon h is:

$$\hat{\tau}_{t+h}^j = \alpha^h + \beta^h \text{Selic}_t + \sum_{k=1}^4 \gamma_k^h \hat{\tau}_{t-k}^j + u_{t+h}, \quad (2.21)$$

where $\hat{\tau}_t^j$ is the MCT permanent trend of food group $j \in \{\text{Food, Food Home, Food Away}\}$ and $\beta^h < 0$ indicates that monetary policy anchors the permanent trend. The inverse specification is:

$$\text{Selic}_{t+h} = \alpha^h + \beta^h \hat{\tau}_t^j + \sum_{k=1}^4 \gamma_k^h \text{Selic}_{t-k} + u_{t+h}, \quad (2.22)$$

where $\beta^h > 0$ indicates that the Copom raises the Selic in response to a rise in the permanent trend of group j . Standard errors are Newey-West (4 lags) or HC3-robust, chosen by the Breusch-Godfrey LM test at $h = 0$ (5% level). The sample runs from February 2003 to April 2026 ($T = 279$).

Table 2.4 contrasts the baseline coefficient with the controlled estimate at $h = 6$ and $h = 12$ for both exercises. The dynamic response is qualitatively robust to the inclusion of macroeconomic controls in every case. In the direct exercise (Panel a), the controlled coefficients are systematically smaller in absolute value than the baseline, by 0.002 to 0.007 percentage points across the three food groups and both horizons, and the sign and the ordering across groups (Food Home largest, Food Away smallest) are unchanged. In the inverse exercise (Panel b), the controlled coefficients are also systematically smaller than the baseline, by 0.045 to 0.308 percentage points, with Food Away showing the largest attenuation in levels, consistent with its wider confidence band documented in Figure 2.4. In both panels, the controlled path lies within the 95% confidence interval of the baseline at every horizon and for every food group, so the two specifications are not statistically distinguishable.

Table 2.4 – Local Projections: Sensitivity to Macroeconomic Controls

Group	(a) Selic is the shock, Trend responds				(b) Trend is the shock, Selic responds			
	$h = 6$		$h = 12$		$h = 6$		$h = 12$	
	Baseline	+Controls	Baseline	+Controls	Baseline	+Controls	Baseline	+Controls
Food	−0.036 (0.005)	−0.030 (0.010)	−0.033 (0.006)	−0.031 (0.011)	1.452 (0.208)	1.348 (0.217)	2.621 (0.412)	2.537 (0.427)
Food Home	−0.051 (0.012)	−0.044 (0.012)	−0.047 (0.014)	−0.043 (0.014)	1.006 (0.167)	0.943 (0.170)	1.765 (0.324)	1.720 (0.333)
Food Away	−0.012 (0.004)	−0.009 (0.005)	−0.013 (0.005)	−0.009 (0.005)	2.360 (0.716)	2.052 (0.476)	3.503 (1.548)	3.253 (0.902)

Notes: Panel (a): response of own-group MCT trend at $h = 6$ and $h = 12$ to a 1 p.p. Selic shock (Equation 2.21). “Baseline” omits macro controls; “+Controls” adds contemporaneous inflation expectations, the output gap (HP-filtered IBC-Br) and the exchange rate variation (Δe). Panel (b): response of the Selic at $h = 6$ and $h = 12$ to a 1 p.p. shock in each food group MCT trend (Equation 2.22), with the same “Baseline” vs. “+Controls” distinction. These controls are post-treatment channels of the respective shocks, so the preferred specification omits them; both panels are reported only as sensitivity checks. The controlled estimate lies within the 95% confidence interval of the baseline at every horizon and for every food group. Newey-West/HC3-robust standard errors in parentheses. Sample: Feb/2003–Apr/2026 ($T = 279$).

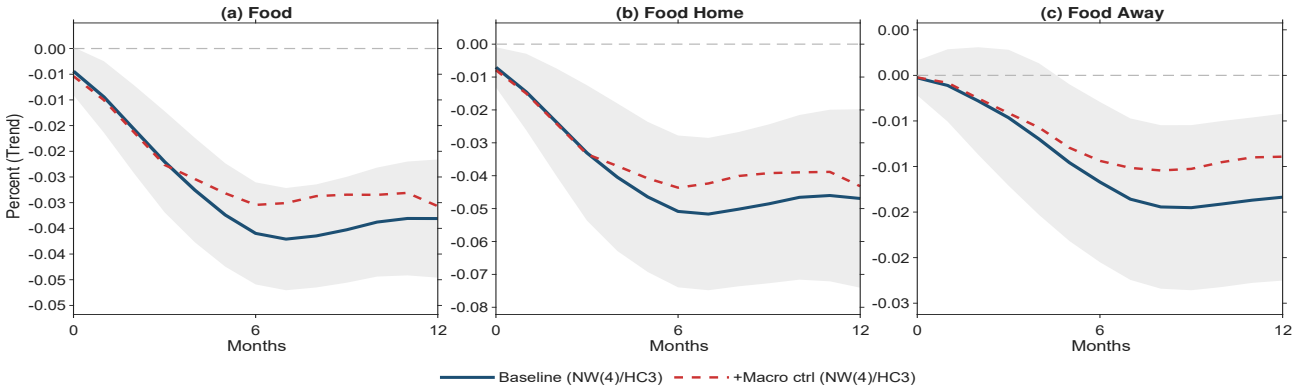
Figure 2.4 reports the impulse response functions with 95% confidence bands. Panel (a) shows the direct responses: all three food groups display a negative response to the Selic shock,

with Food Home exhibiting the largest magnitude and Food Away the smallest and least precise response, whose confidence band overlaps zero at most horizons, indicating that monetary policy transmits poorly to the permanent trend of food services. Panel (b) shows the inverse responses: all three groups display a positive and rising Selic reaction; Food Away generates the largest reaction at $h = 12$ despite its smaller basket weight, consistent with its higher permanent shock connectedness documented in Section 2.6.1.

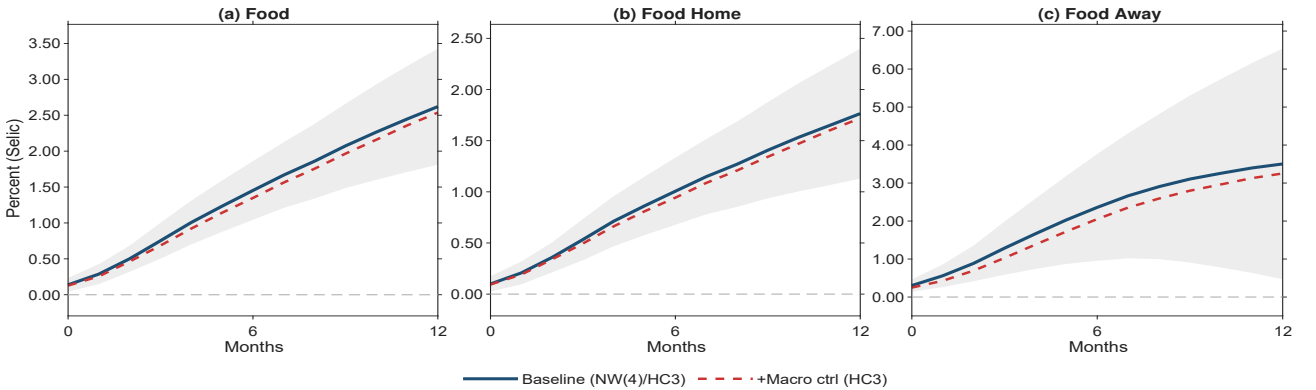
As a sensitivity check, we augment Equation (2.21) and Equation (2.22) with contemporaneous inflation expectations, the output gap (HP-filtered IBC-Br) and the log-change in the exchange rate. We stress that this is a sensitivity check rather than our preferred specification: these three variables are post-treatment channels through which a Selic shock propagates to the food trend, and through which the food trend propagates to the Selic, so including them risks partialling out part of the effect β^h is meant to capture. We report the exercise precisely to show that this concern does not overturn the results. Estimation uses Newey-West or HC3-robust standard errors, chosen as described above, on the common sample ($t \geq 13$).

Figure 2.4 – Local Projections: Selic and Food Inflation Trends

(a) Selic is the shock, Trend responds



(b) Trend is the shock, Selic responds



Notes Panel (a): response of each food group MCT trend to a 1 p.p. Selic shock (Equation 2.21); impulse response negative. Panel (b): response of the Selic to a 1 p.p. shock in each food group MCT trend (Equation 2.22); impulse response positive. Solid blue: baseline; dashed red: specification augmented with contemporaneous inflation expectations, output gap and exchange rate variation. Shaded bands: 95% Newey-West/HC3 confidence interval of the baseline. Sample: Feb/2003–Apr/2026 ($T = 279$).

Two points reinforce this interpretation. First, the modest and one-directional attenuation observed when the macro controls are added indicates that the Selic shock does not transmit to the permanent food trend solely through these contemporaneous channels; a substantial part of the effect operates directly, consistent with the broad-based transmission documented in the

baseline. Second, because the controlled and uncontrolled estimates remain close, the baseline response is not attributable to omitted macroeconomic factors correlated with the Selic shock or with the food trend. The preferred specification nonetheless remains the parsimonious baseline of Equations (2.21) and (2.22); the augmented specification serves only to demonstrate robustness.

2.7 Conclusion

This paper analyzed food inflation persistence in Brazil from August 1999 to May 2026, using the Multivariate Core Trend (MCT) as the primary framework. The MCT extends the Multivariate Unobserved Components Stochastic Volatility with Outliers (MUCSVO) of Stock, and Watson (2016), following Almuzara, and Sbordone (2022) and Almuzara, and Sbordone (2024), by letting the transitory component follow a moving-average process instead of white noise. By combining the MCT with a complementary TVP-VAR-DY connectedness analysis and a local projection exercise, we confirmed our central hypothesis: food inflation dynamics in Brazil are structurally heterogeneous, exposing Food at Home to a disproportionately growing structural persistence relative to Food Away From Home.

The MCT permanent volatility component revealed a divergent historical trajectory since 1999, characterized by a pronounced structural split between the two food subcomponents. Food at Home faces a permanent volatility that grew from 0.21 to 0.22 over the sample and produced a posterior outlier probability of 0.87 in December 2019, 0.65 in November 2002, and 0.63 in June 2018. This upward trajectory explains why the twelve month accumulated trend for Food at Home reached peaks of 24.83% in May 2003 and 14.25% in July 2008, before falling to a trough of -3.06% in 2017 and rising again to 14.80% in February 2021. Food Away From Home displayed the opposite pattern, with permanent volatility falling from 0.14 to 0.13 and trend peaks of 14.55% in July 2003, 12.21% in October 2008, 10.54% in November 2015, and only 7.82% in February 2023. Furthermore, the timing of these peaks relative to Food at Home was irregular across episodes, ranging from a lag of a few months to a lag of several years and, in one episode, leading rather than lagging, indicating a fast contemporaneous transmission and a slower unwinding rather than a fixed transmission lag.

The complementary connectedness analysis highlighted an asymmetric transmission mechanism throughout the food inflation system. While the permanent volatility of Food Away From Home acted as the system’s primary uncertainty absorber across the entire sample, intensifying rather than reversing over time, the permanent volatility of Food at Home switched regime in the Post-COVID period, turning into a net transmitter of systemic uncertainty for the first time in the sample. Furthermore, the local projection exercise, which augments the baseline specification with contemporaneous macroeconomic controls as a robustness check, confirmed that this pattern is not driven by omitted variables: the sign and the ordering of the responses across food groups remained unchanged, and the controlled estimates stayed within the 95% confidence interval of the baseline at every horizon.

From a policy perspective, these findings reveal the inherent limitations of a central bank strategy that treats food price shocks uniformly as transitory. By demonstrating that the permanent volatility of Food at Home becomes a net transmitter of systemic uncertainty precisely in the Post-COVID period, the only episode in the sample in which this occurs, this study uncovers a structural shift that a monetary policy strictly guided by the headline IPCA would fail to detect in real time. A central bank that continues to treat the domestic food subcomponent as uniformly transitory risks allowing persistent, high probability outlier episodes in Food at Home to become embedded in the permanent trend before a monetary response is warranted.

Despite its contributions, this study is subject to certain limitations that open promising avenues for future research. Although the MCT framework efficiently isolates common and sector specific dynamics for the food subcomponents considered, it does not yet incorporate the physical drivers of agricultural supply shocks. A natural extension is the incorporation of climate variables into the MCT model, which would allow identifying the specific channels through which agricultural supply shocks are transmitted to the permanent component of Food at Home. Alternatively, another promising avenue for future research is the investigation of regional heterogeneity in food inflation persistence in Brazil, following the approach of Apergis (2025) for United States metropolitan areas, given the size and economic diversity of the country.

Consequently, we propose that the Brazilian Central Bank monitor the posterior outlier probability of Food at Home as an early warning indicator within its operational framework. When this probability remains elevated for two or three consecutive months, the model signals that the shock is being absorbed as a transitory disturbance and is not contaminating the permanent trend, supporting a non interventionist monetary policy stance. When the probability returns to low levels while the trend remains elevated, the model indicates that the shock has been incorporated into the permanent component and warrants a monetary policy response. Acknowledging this structural asymmetry between Food at Home and Food Away From Home is a technical requirement to improve the timing and precision of monetary policy interventions in Brazil.

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Appendix

Table A1 – Descriptive Statistics: Local Projection Variables (% month)

Variable	Mean	Median	Max	Min	Std. Dev.
Selic (% p.a.)	11.61	11.50	26.50	2.00	4.57
Food Trend	0.56	0.55	1.79	−0.36	0.39
Food at Home Trend	0.54	0.50	2.01	−0.65	0.50
Food Away from Home Trend	0.61	0.59	1.20	0.16	0.22
Inflation Expectations	0.42	0.41	1.28	−0.13	0.14
IBC-Br	0.00	0.00	0.04	−0.14	0.02
Exchange Rate	0.00	0.00	0.09	−0.15	0.03

Source: BCB, IBGE/SIDRA. Notes: Sample Jan/2003–Apr/2026.

Table A2 – Unit Root and Structural Break Tests: Local Projection Variables (% month)

Variable	ADF	PP	KPSS	Zivot–Andrews		Decision
				Stat.	Break date	
Selic (% p.a.)	−3.03**	−3.24**	1.44***	−3.85	2021m07	I(1)
Food Trend	−3.40**	−5.20***	0.11	−4.30	2016m07	I(0)
Food at Home Trend	−3.47***	−5.24***	0.11	−4.09	2016m07	I(0)
Food Away from Home Trend	−2.26	−3.89***	1.26***	−4.56	2016m01	I(1)
Inflation Expectations	−2.67*	−10.31***	0.37*	−3.75	2016m12	I(0)
IBC-Br	−5.27***	−5.07***	0.07	−6.10***	2015m03	I(0)
Exchange Rate	−5.09***	−12.37***	0.29	−5.96***	2021m03	I(0)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: BCB, IBGE/SIDRA. Notes: H_0 : unit root (ADF, PP) or stationarity (KPSS).

3 INFLATION PERSISTENCE AND CLUB CONVERGENCE: A REGIONAL ANALYSIS OF THE BRAZILIAN CASE

Abstract

This paper investigates regional price dynamics in Brazil, focusing on inflation persistence and convergence from January 2003 to November 2024. Through the application of Time-Varying Parameter (TVP) models and Club Convergence analysis, this study assesses regional inflation rates in eleven major metropolitan areas: Belém, Belo Horizonte, Brasília, Curitiba, Fortaleza, Goiânia, Recife, Salvador, Rio de Janeiro, São Paulo, and Porto Alegre. The results reveal significant heterogeneity in price dynamics. Specifically, low inflation persistence is observed in São Paulo, Salvador, Belém, and Brasília, whereas Curitiba exhibits high persistence, a characteristic that was further accentuated by the COVID-19 pandemic. The COVID-19 pandemic increased inflationary inertia in Recife, Belo Horizonte, Rio de Janeiro, and Curitiba, while Fortaleza remained unaffected. Although aggregate regional CPI (IPCA) headline inflation rates show no evidence of overall convergence, a global convergence pattern emerges when analyzing sectorally disaggregated data. These findings suggest that despite Brazil's continental dimensions, sectoral inflation components share common underlying drivers that facilitate long-run convergence.

Keywords: CPI Index; Kalman Filter; Phillips and Sul; Inertia; Convergence.

JEL Classification: E31; C32; R11

3.1 Introduction

Inflation is a cornerstone of macroeconomic stability, influencing everything from monetary policy formulation to the economic well-being of the population. While national monetary policy relies on aggregate indicators, its transmission is inherently tied to underlying regional price dynamics. In a country of continental dimensions like Brazil, territorial disparities in infrastructure, logistics, and consumer behavior implies that a ‘one-size-fits-all’ policy may yield asymmetric results across different regions. Consequently, the traditional assumption of regional price homogeneity frequently fails to capture the complexities of subnational price fluctuations.

The objective of this study is to analyze the dynamics of Brazilian inflation by investigating the heterogeneity of persistence and the formation of convergence clubs across eleven major cities: Belém, Belo Horizonte, Brasília, Curitiba, Fortaleza, Goiânia, Recife, Salvador, Rio de Janeiro, São Paulo, and Porto Alegre. To identify whether price synchronization occurs uniformly or is contingent upon specific consumption groups and regional characteristics, we disaggregate regional inflation into nine components: housing, household items, clothing, transportation, health and personal care, personal expenses, education, communication, and food and beverages (the latter further divided into “food at home” and “food away from home”). The empirical strategy employs Time-Varying Parameter (TVP) models and Club Convergence estimations, from January 2003 to November 2024. By addressing these gaps, this study reveals an aggregation bias in Brazil’s inflationary memory and demonstrates that price synchronization is a sectoral rather than a global phenomenon.

The central hypothesis of this study is that Brazilian inflation presents a dual structural heterogeneity that conditions the transmission of monetary policy. We posit, first, that inflation persistence is time-varying and subject to an ‘aggregation bias’, where national measures mask localized inertia. Second, we hypothesize that price convergence in Brazil is not a global phenomenon but a sectoral one, occurring predominantly within specific ‘clubs’ where integrated supply chains and common cost shocks override regional idiosyncratic factors.

Our findings confirm significant disparities in inflation persistence across Brazilian cities. A time-varying Phillips Curve analysis indicates that national headline inertia often equals or exceeds regional levels, reinforcing the existence of an aggregation bias in Brazil’s inflationary dynamics. Furthermore, the degree of persistence varies widely by location: São Paulo, Salvador, Belém, and Brasília exhibit low inflationary inertia, while Curitiba stands out with a high persistence level. Also, the COVID-19 pandemic appears to have intensified inflation inertia in Recife, Belo Horizonte, Rio de Janeiro, and Curitiba, whereas Fortaleza remained largely unaffected. Regarding convergence, the club estimations show no evidence of a single global trend among the eleven cities. However, specific convergence is identified in household items and transportation. Conversely, a pattern of transitional divergence and turn-around, a weaker form of convergence, characterizes communication and food-related groups. This transitional behavior also predominates in the convergence clubs formed by other sectoral rates, with only one exception.

Besides this Introduction, Section 2 provides the literature review. Section 3 describes the dataset. Section 4 outlines the econometric methodologies and estimated equations. Section 5 presents the empirical results. Finally, Section 6 concludes the study and proposes policy recommendations.

3.2 Literature

3.2.1 *Inflation Persistence: Theoretical Framework and Empirical Evidence*

The theoretical debate on inflation persistence has evolved through various macroeconomic lenses, ranging from structuralist perspectives to the modern consensus. In the 1970s, the Post-Keynesian (PK) tradition emerged as an alternative to the neoclassical consensus, framing inflation as a persistent process resulting from conflicts over income distribution (Lee, 2009). Within this framework, as developed by Rowthorn (1977) and more recently by Hein (2023), inflation stems from incompatible distributive claims between economic agents. These models, supported by works such as Hein (2006), Hein (2008), and Stockhammer (2008), suggest that current price behavior is heavily influenced by how inflation expectations and inertia are embedded in wage demands and contracts.

Parallel to this, the mainstream discussion on inflation dynamics was built upon the framework of the Phillips Curve, examining the trade-off between inflation and unemployment. The literature developed with contributions from Friedman (1961), and his backward-looking model, followed by Calvo (1983), whose forward-looking model provided one of the first equations for the New Keynesian Phillips Curve. Subsequent research by Galí, and Gertler (1999), Clarida, Gali, and Gertler (1999), and Blanchard, and Galí (2007) refined these models by incorporating both backward and forward-looking components to account for price and real wage rigidities. Further contributions by Mankiw, and Reis (2002) introduced the concept of information rigidity, and Woodford, and Walsh (2005) modified the model to include partial price adjustments based on lagged inflation, providing a micro-founded basis for why inflation sustains its trajectory over time.

In the Brazilian context, the discussion on inflation persistence gained a unique dimension due to the country's history of high inflation and indexation. Bresser-Pereira, and Nakano (1986) and Bresser-Pereira, and Nakano (1987) argued that Brazil's economic profile in the 1980s and 1990s led to specific factors related to inertial inflation. This study aligns with the concept of intrinsic persistence, defined by Fuhrer (2010) as the tendency of an indicator to sustain its current trajectory unless influenced by external factors. Additionally, Angeloni et al. (2006) identifies other dimensions of persistence: i) expectations persistence; ii) error term persistence; and iii) extrinsic persistence, related to fluctuations in the output gap.

Recent literature highlights that inflation inertia is far from a uniform national phenomenon, exhibiting profound heterogeneity when disaggregated into regional and metropolitan levels. For instance, G. Caporale, L. Gil-Alana, and Poza (2022) examined long-range depen-

dence in the inflation rates of G7 countries over the period from January 1973 to March 2020 using a fractional integration framework. By estimating the (fractional) order of integration, they found that inflation series are highly persistent and that, after accounting for endogenous structural breaks, significant differences emerge between countries and sub-periods, likely reflecting distinct levels of monetary authority reputation and credibility.

Extending this investigation to the European context, G. Caporale, Infante, et al. (2023) analyzed the persistence of inflation in both the Eurozone and the EU27, using monthly data spanning from September 1997 to August 2022. Their research also stressed the impacts of the COVID-19 pandemic and the Russia-Ukraine war, employing fractional integration models combined with recursive and rolling estimation methods. Their full-sample results suggested that shocks had long-lasting but ultimately temporary effects. As for the recursive estimations, they revealed a significant upward trend in persistence, particularly for the EU27. The authors' evidence reinforced the idea that the intensity of such systemic disruptions requires policy responses that account for the shifting nature of inflationary memory.

Specifically focusing on the subnational scale, Apergis (2025) provided compelling evidence that inflation persistence varies significantly across 23 US metro areas. Through a Multivariate Unobserved-Components Stochastic Volatility (MUCSVO) model covering the post-pandemic period (2020-2024), the study identifies strong persistent patterns in nearly half of the areas, suggesting that national aggregates may misrepresent local inflationary risks. Ebuh et al. (2023) highlighted the divergent contributions of urban and rural inflation to total inertia in Nigeria, utilizing fractional integration and cointegration methods on data from 1995 to 2022 to show that rural shocks often possess longer-lasting effects than urban ones.

Aslanidis, Koursaros, and Otto (2024) examined the asymmetric nature of inflation persistence across five major inflation-targeting economies Australia, New Zealand, Sweden, the United States, and the Euro Area, using monthly data spanning from 1990 to 2023. The authors employed a Threshold Autoregressive (TAR) model and found that persistence reacts non-linearly depending on the inflation level relative to the Central Bank's target. Specifically, their empirical results demonstrated that inflation is significantly more persistent when it remains below the target than when it exceeds it. This evidence suggests that the effectiveness of uniform monetary policy responses is compromised by the 'dual nature' of inflationary memory, which shifts dynamically along the business cycle.

Empirical studies globally support the existence of such spatial disparities. Benigno, and Lopez-Salido (2006) found significant differences in persistence across the European Monetary Union, while Coleman (2010) found evidence of asymmetry in the African Financial Community. Romero-Ávila, and Usabiaga (2011) identified robust evidence of high persistence in Spain with significant regional heterogeneity. Similar patterns have been reported by Gerlach, and Tillmann (2012) for the Asia-Pacific region, Vaona, and Ascari (2012) for Italian regions, Tillmann (2013) for South Korea, and Gajewski (2018) for Poland. Furthermore, Di Bartolomeo, Di Pietro, and Beqiraj (2020) found intrinsic price and wage inertia across seven advanced economies,

and Duran, and Dindaroglu (2021) found that persistence across 26 Turkish regions is both heterogeneous and spatially correlated.

Brazilian researchers have also contributed to the discussion, from the structuralist-monetarist controversy (H. C. I. Pereira, and A. R. d. Carvalho, 2019) to the subsequent focus on inertia (Arida, and Lara-Rezende, 1985; Bresser-Pereira, 2023). Regarding the regional inflation case, Caetano, Ferreira, and Silva Jr (2009) identified considerable disparities in inflation persistence across Brazilian metropolitan areas, for the period ranging from August 1994 to October 2008. Although the study finds an overall high level of inertia across the country, the author demonstrates that the magnitude and duration of inflationary shocks are far from uniform. By highlighting these regional asymmetries, Caetano, Ferreira, and Silva Jr (2009) argued that such persistent disparities can hinder the effectiveness of a centralized monetary policy, as localized price rigidities may prevent a synchronized return to the inflation target.

Building upon this evidence, Gomes da Silva, and Vieira (2013) investigated this phenomenon for the period from January 1995 to December 2011, analyzing eleven major metropolitan areas through Auto-Regressive Fractionally Integrated (ARFIMA) models. Their findings provide evidence of persistence characterized by stationarity and long-run mean reversion, yet they reveal that inflation in Brazilian capitals exhibits distinct inflationary memories. By identifying regions with higher sensitivity to structural breaks and localized shocks, the authors demonstrate that these varying persistence levels reflect an asymmetric inflationary dynamic across the country.

This diversity in persistence is further supported by data from the Central Bank of Brazil (BCB) (BCB, 2017), which highlight a significant regional variance in disinflation speeds. While the Southern region experienced a faster convergence to lower price levels, the North and Northeast lagged behind. Specifically, cities such as Belém and São Paulo have been identified as exhibiting the highest and lowest persistence rates, respectively, suggesting that a unified monetary policy may encounter asymmetric responses across the territory.

In the Brazilian context, A. F. Silva, Carrara, and Castro (2024) document significant heterogeneous persistence across various product groups by utilizing a Time-Varying Parameters (TVP) model applied to monthly data from January 2000 to December 2023. By estimating the evolution of autoregressive coefficients over time, their research reveals that inflationary memory is not uniformly distributed across the IPCA basket. Specifically, they find that services and regulated prices often act as structural anchors of inertia due to indexation mechanisms and contract rigidity. In contrast, volatile items, such as fresh food and energy, exhibit rapid mean reversion, reacting swiftly to market changes and supply shocks. This sectoral divergence suggests that aggregate inflation persistence in Brazil is a weighted average of highly disparate micro-dynamics, supporting the claim that a localized or sectoral approach is essential for a more accurate diagnostic of national price stability.

The documented regional heterogeneity of Brazilian inflation is fundamentally linked to its varying degrees of persistence, as shocks to the price level do not dissipate at the same rate

across different metropolitan areas. These persistent disparities in price adjustment suggest that regional inflationary processes may lead to fragmented long-term behaviors rather than a synchronized national movement. By establishing that such inflationary memories and disinflation speeds are asymmetric, the existing literature sets the stage for investigating whether these divergent paths eventually culminate in a unified national steady state or in the formation of specific convergence clubs.

3.2.2 Economic and Price Convergence: Theoretical and Empirical Foundations

The hypothesis of economic convergence, rooted in the neoclassical growth models of Solow (1956), posits that economies with lower per capita incomes tend to grow more rapidly than those with higher incomes, eventually reaching a similar steady state. While Myrdal (1957) initially challenged this with the concept of circular cumulative causation, the literature evolved toward more nuanced interpretations. Baumol (1986) pioneered the idea of convergence clubs, describing groups of economies that gravitate toward different equilibrium points. This was further expanded by Barro, and Sala-i-Martin (1997), who incorporated technological diffusion and advocated for conditional convergence, where economies converge only if they share similar structural characteristics.

In the realm of prices, convergence is fundamentally associated with the law of one price, which refers to the notion that, in an efficient market, the price of identical goods must be the same when expressed in a common currency. Evidence of this remains a subject of intense debate and is considered a persistent puzzle in macroeconomics. Analyzing price convergence within a single country offers a unique laboratory to study market integration, regional productivity differentials, and the asymmetric impacts of a centralized monetary policy (Cecchetti, Mark, and Sonora, 2000). Furthermore, such analysis serves to clarify structural features, such as the degree of market integration among regions, the regional composition of input factors, and the role of regional inflation dynamics.

The methodological landscape for detecting these dynamics shifted significantly with the work of Quah (1996), who utilized Markov chain models to identify income distribution clusters. Subsequent spatial and multivariate approaches, such as those by Le Gallo, and Dall'erba (2006) and Corrado, Martin, and Weeks (2005), paved the way for the seminal contribution of Phillips, and Sul (2007) and Phillips, and Sul (2009). They proposed a time-varying factor model and the log-t test to identify convergence clubs, allowing the systematic idiosyncratic element to evolve over time. This methodology provided a more robust analysis of economic trajectories and club formation by addressing issues of heterogeneity and non-stationarity.

Regarding regional price convergence, recent research increasingly suggests that headline inflation rates often conceal fundamental spatial divergences. F. Pereira, and Aguiar-Conraria (2025) and Škare, Gavurova, and Sinković (2023) warn that aggregate convergence can be 'deceptive,' as simultaneous processes of regional catching-up and divergence often coexist. The application of club convergence models has been instrumental in identifying these spatial pat-

terns; Maynou et al. (2021) and Bareith, and Fertő (2025) demonstrate how regional housing and food prices in the EU form distinct clusters based on local macroeconomic fundamentals. Evidence from the US (Becsi, and Ige, 2025), Russia (Lepekhin, 2024), and Sri Lanka (Perera, Jangam, and Rath, 2025) further confirms that while trade integration facilitates long-run convergence, regional idiosyncrasies and gravity variables (Yilmazkuday, 2023) are critical determinants of price clubs. Collectively, these studies emphasize that analyzing inflation through a regional lens is essential to understanding the true dynamics of price stability, as sectoral and metropolitan disparities frequently override national trends.

Empirically, the notion of convergence clubs has been explored across various other fields, including CO_2 emissions (Panopoulou, and Pantelidis, 2009), eco-efficiency (Camarero et al., 2013), housing prices (Nagayasu, 2011; Montanes, and Olmos, 2013), and corporate taxes (Regis, Cuestas, and Y. Chen, 2015). Regarding inflation specifically, Cuestas, L. A. Gil-Alana, and Taylor (2016) found that most Central and Eastern European countries converge to a common steady-state rate. Additionally, Christou, Cunado, and Gupta (2019) and Aginta (2020) demonstrated that price indices and their groups often form distinct regional clusters. More recently, Fan et al. (2023) examined international food price inflation across 198 countries, finding limited evidence of overall convergence but strong evidence of club formation linked to economic development and social stability.

In the Brazilian context, while the convergence approach has been extensively applied to studies on income (Gondim, Barreto, and J. R. Carvalho, 2007; Coelho, and L. D. Figueiredo, 2007; Penna, and Linhares, 2017; Rosa, and A. M. R. Figueiredo, 2023), well-being (Penna, Linhares, et al., 2013), and technological progress (Penna, and Linhares, 2017), a significant gap remains regarding the regional analysis of inflation for the price index and its groups. Most existing studies overlook the sectoral disaggregation under the econometric framework of Phillips, and Sul (2007) and Phillips, and Sul (2009). In this regard, the present study aims to contribute to the understanding of this phenomenon by investigating whether Brazil's regional price dynamics are characterized by global integration or fragmented into specific sectoral convergence clubs.

Despite the absence of studies employing the Phillips-Sul framework for regional inflation groups, recent research has explored these dynamics through alternative, yet highly relevant, lenses. For instance, Lucena (2025) provides a comprehensive analysis of the inflationary process in Brazil, focusing on group-level, structural, and regional dynamics to highlight distinct yet complementary aspects of inflation. In the third chapter of this thesis, the author examines the synchronization between metropolitan regional inflation and the national IPCA from January 2000 to August 2024 using Continuous Wavelet Transform (CWT). The results demonstrate that while regional inflation is highly synchronized with the national index in long-term cycles (4 to 8 years), with coherence areas exceeding 80%, this relationship is significantly weaker in the short term (6 to 12 months), where synchronization fluctuates between 30% and 60%, particularly in the North and Northeast. For example, Recife and Fortaleza exhibit notably lower short-term synchronization (34.66% and 56.53%, respectively) compared

to the high stability found in São Paulo and Porto Alegre. By identifying these non-linear co-movements and the lack of a clear national leader in the long run, Lucena (2025) suggests that regional asymmetries, where specific periods show the Northeast leading national movements while the Southeast remains more passive, pose substantial challenges for a unified monetary policy, as national shocks do not impact all regions uniformly across different time scales. These results of time-dependent synchronization justify the use of the Phillips and Sul (2007, 2009) methodology in this study, as it is specifically designed to identify club formation amidst such regional asymmetries.

Filling this gap, the present research contributes to the literature in three ways. First, it employs TVP models to demonstrate that national inflation inertia often masks localized disparities (aggregation bias). Second, it advances the convergence debate by proving that price synchronization is a sectoral rather than a global phenomenon, occurring within specific commodity clubs. Finally, it quantifies the heterogeneous impact of the COVID-19 pandemic on inflationary memory across eleven metropolitan areas, providing a post-crisis analysis that is still scarce in the subnational literature

3.3 Data

Our empirical analysis utilizes monthly data from January 2003 to November 2024, all of which are seasonally adjusted. The variables are defined as follows:

- π_t^L : Consumer Price Index (IPCA) for Brazil and 11 major metropolitan areas $L = 1, \dots, 12$, with the full list of locations reported in Table 3.3. Source: IBGE.
- $E_t\pi_{t+1}$: Inflation Expectations (one-month ahead). Source: BCB.
- y_t : Central Bank's Economic Activity Index - IBC-Br (log-transformed and detrended via the Hodrick-Prescott (HP) filter). Source: BCB.
- Δe_t : Real Effective Exchange Rate (2020=100; adjusted; log-transformed in first differences). Source: BIS.

The Brazilian Consumer Price Inflation (CPI-IPCA) encompasses 16 cities and metro areas from the five regions of the country: i) North (Belém, Rio Branco); ii) Northeast (Aracaju, Fortaleza, Recife, Salvador, São Luís); iii) Central-West (Brasília, Campo Grande, Goiânia); iv) Southeast (Belo Horizonte, Rio de Janeiro, São Paulo, Grande Vitória); v) South (Curitiba, Porto Alegre). However, certain locations, specifically Aracaju, Campo Grande, Rio Branco, São Luís, and Grande Vitória, were only recently incorporated into the index. Their shorter historical series limit the viability their inclusion in our econometric estimations. Despite these exclusions, the 11 remaining cities analyzed in this study account for approximately 93 percent of the total IPCA basket, ensuring high national representativeness.

Table 3.1 – Regional CPI-IPCA Inflation (% month) - Descriptive Statistics and Regional Weights

Sample	Mean	Median	Max	Min	Std. Dev.	Regional Weights (%)
CPI - Brazil	0.475	0.427	1.959	-0.563	0.310	100.00
CPI - Rio de Janeiro	0.483	0.465	2.020	-0.310	0.348	9.43
CPI - São Paulo	0.466	0.411	2.176	-0.516	0.319	32.28
CPI - Belo Horizonte	0.494	0.464	2.126	-0.762	0.351	9.69
CPI - Brasília	0.469	0.428	1.986	-0.907	0.412	4.06
CPI - Fortaleza	0.495	0.441	1.911	-0.625	0.384	3.23
CPI - Recife	0.483	0.464	2.130	-1.203	0.380	3.92
CPI - Salvador	0.468	0.430	2.400	-0.955	0.407	5.99
CPI - Belém	0.485	0.470	1.572	-1.212	0.364	3.94
CPI - Goiânia	0.471	0.476	1.824	-1.880	0.454	4.17
CPI - Curitiba	0.471	0.446	2.074	-1.401	0.443	8.09
CPI - Porto Alegre	0.468	0.432	1.828	-0.801	0.393	8.61
Inflation Expectations	0.415	0.420	1.186	-0.098	0.126	–
Real Exch. Rate (Δe_t)	0.001	0.003	0.094	-0.154	0.031	–
Economic Activity (y_t)	0.000	0.350	4.487	-18.801	2.666	–

Source: IBGE. Note: Regional weights not considered in the research: CPI -Aracaju (1.03), CPI -Campo Grande (1.57), CPI - Rio Branco (0.51), CPI - São Luís (1.62), CPI - Grande Vitória (1.86).

Table 3.3 reports the descriptive statistics for regional inflation and the control variables. The rightmost column displays the regional weights as of November 2024, where the gap to 100% reflects the exclusion of the five aforementioned cities. The data reveals significant heterogeneity in price dynamics across the 11 locations, providing preliminary evidence for our central hypothesis.

While Fortaleza exhibits the highest average monthly inflation (0.495), São Paulo presents the lowest (0.466). This discrepancy suggests that the national anchor is heavily influenced by the Southeast’s performance (32.28% weight), potentially masking localized inflationary pressures in smaller regions, a core premise of our ‘aggregation bias’ argument.

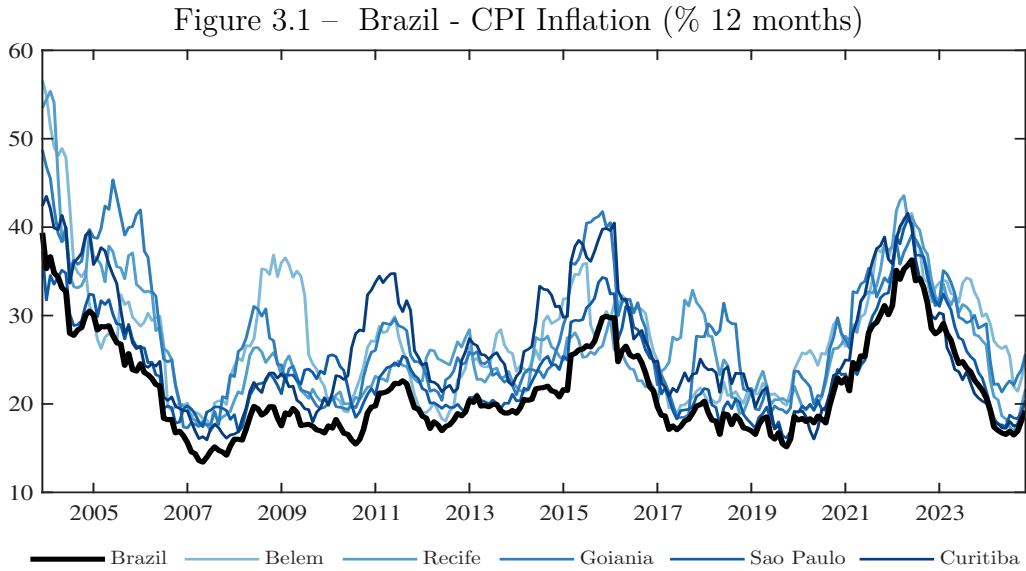
A closer look at the second moments shows that Goiânia and Curitiba stand out with the highest volatility (0.454 and 0.443, respectively). In Goiânia’s case, the wide range between the maximum (1.824) and minimum (-1.880) points to a high sensitivity to supply-side or idiosyncratic shocks. Furthermore, for most cities, the mean exceeds the median, suggesting a right-skewed distribution characterized by frequent inflationary spikes. This distributional asymmetry reinforces our hypothesis of a ‘dual nature’ in Brazilian inflation: while cities may share a common national trend, their individual persistence and response to shocks (inertia) are structurally diverse. Such disparities justify the use of Time-Varying Parameter (TVP) models to capture how these localized dynamics evolve differently from the aggregate national pattern.

Figure 3.1 displays the 12-month accumulated IPCA inflation for the period under study, featuring one representative city from each of Brazil’s five geographical regions: (i) Belém (North); (ii) Recife (Northeast); (iii) Goiânia (Central-West); (iv) São Paulo (Southeast); and (v) Curitiba (South). These locations were selected based on their specific volatility profiles (standard deviations) reported in Table 3.3.

Using the national IPCA as a benchmark, the visual evidence reveals a co-movement in regional inflation trajectories, yet with persistent localized deviations that support our central

claim of regional heterogeneity. These fluctuations are marked by three major systemic shocks. The first, in 2002-2003, stemmed from market uncertainty surrounding the presidential transition and its potential impact on fiscal credibility. The second, peaking in 2016, resulted from the collapse of the ‘New Economic Matrix’, a policy framework that triggered severe macroeconomic imbalances and price hikes. Finally, the COVID-19 pandemic introduced a global supply-demand mismatch that affected all regions, notwithstanding with varying intensities (Gomes da Silva, and Fishlow, 2021).

While these shocks hit the country as a whole, the widening gaps between regional lines during these episodes suggest that persistence and convergence are not uniform. Such visual disparities reinforce our hypothesis that national aggregate measures may mask significant subnational inertia, justifying the application of time-varying models to capture these evolving dynamics.



To streamline the presentation, we focused our descriptive statistics and graphical analysis on the headline indicators. However, to address the question of sectoral convergence, we decompose the IPCA for each city into its nine official categories: (i) food and beverages; (ii) housing; (iii) household items; (iv) clothing; (v) transportation; (vi) health and personal care; (vii) personal expenses; (viii) education; and (ix) communication. In addition, the ‘food and beverages’ group is further partitioned into ‘food at home’ and ‘food away from home’. This distinction allows us to isolate price movements driven by typical supply-side shocks (food at home) from those more sensitive to demand-side pressures (food away from home), providing a detailed perspective on the sectoral convergence patterns postulated in our study.

3.4 Econometric Approach

3.4.1 Time-Varying Parameter (Kalman Filter)

To investigate regional inflation dynamics, we estimate an Augmented Phillips Curve specified as follows:

$$\pi_t^L = \alpha_0 + \alpha_1\pi_{t-1} + \alpha_2 E\pi_{t+1} + \alpha_3\Delta e_{t-4} + \alpha_4 y_t + \varepsilon_t, \quad L = 1, \dots, 12 \quad (3.1)$$

In this specification, α_0 represents the intercept, while α_1 , related to lagged inflation π_{t-1} , captures inflation persistence. The impact of forward-looking expectations $E\pi_{t+1}$ on current price-setting is measured by α_2 . The coefficients α_3 and α_4 represent, respectively, the pass-through of exchange rate shocks Δe_{t-4} and the sensitivity of inflation to domestic economic activity y_t . Finally, ε_t is the idiosyncratic error term.

Preliminary Generalized Method of Moments (GMM) regressions serve as a foundational benchmark for the estimation of the Phillips Curve via Time-Varying Parameter (TVP) framework. Specifically, the GMM results provide the initial values, variances, and optimal lag structures required for the subsequent state-space modeling (Hamilton, 1994; Elliott, and Timmermann, 2016). As a robust methodology, the GMM effectively addresses endogeneity in both temporal and cross-sectional dimensions by utilizing instrumental variables to mitigate correlations between regressors and idiosyncratic errors. This approach ensures that the dynamics of explanatory variables and regional effects are accurately captured before advancing to the time-varying parameter recursions.

Following this calibration, the TVP framework via the Kalman Filter (Kalman, 1960) is applied to capture the evolution of parameters over time, adjusting them as economic conditions shift. The Kalman Filter provides an adaptive and precise representation of economic relationships, particularly within the Phillips Curve context, where the link between inflation and its determinants may vary due to structural shocks and policy changes (Hamilton, 1994). Consequently, our Phillips Curve empirical strategy proceeds in two stages. First, we estimate the GMM model to establish a baseline and, subsequently, we apply the TVP-Kalman Filter recursions to the national aggregate and each of the 11 metropolitan areas.

3.4.2 Club Convergence

Our second empirical stage involves a convergence/divergence analysis based on the methodology developed by Phillips, and Sul (2007) and Phillips, and Sul (2009) (hereafter PS) which, unlike traditional tests, does not rely on stationarity assumptions and can identify multiple steady states or transitional divergence. Therefore, the PS technique is particularly suitable for investigating the dual nature of inflation, as it endogenously identifies convergence clubs within a panel and corrects for biases related to unit root properties.

In our framework, the inflation rate for each city $L = 2, \dots, 12$ is represented by the following model proposed by PS:

$$\pi_t^L = \delta_{it}\mu_t, \quad L = 2, \dots, 12 \quad (3.2)$$

where δ_{it} is a time-varying factor coefficient that quantifies the idiosyncratic deviation between the common factor μ_t and the systematic group of π_t^L , which represents consumer price index

data. The Equation 3.2 can be used to analyze convergence by testing whether the factor δ_{it} converges or not. Phillips, and Sul (2007) proposed modeling the transition elements by:

$$h_{it} = \frac{\pi_t^L}{\frac{1}{N} \sum_{i=t}^N \pi_t^L} = \frac{\delta_{it}}{\frac{1}{N} \sum_{i=t}^N \delta_{it}} \quad (3.3)$$

where h_{it} represents the relative transition path, tracing the individual trajectory of each city relative to the panel average. The null hypothesis of convergence derives from the following formulation:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^\alpha} \quad (3.4)$$

where δ_{it} is fixed, $\sigma_i > 0$, ξ_{it} i.i.d (0,1) across i and weakly dependent on t and L tends to infinity as t grows. The L function takes the log-t form. ξ_{it} captures the time-varying and region-specific groups of the model. The size of α determines the behavior of convergence or divergence of δ_{it} . The null hypothesis can be written as:

$$H_0 : \delta_i = \delta, \text{ and } \alpha \geq 0 \quad (3.5)$$

The alternative hypothesis assumes the following form:

$$H_A : \delta_i = \delta, \text{ for all } i \text{ with } \alpha < 0 \quad (3.6a)$$

$$H_A : \delta_i \neq \delta \text{ for some } i \text{ with } \alpha \geq 0, \text{ or } \alpha < 0 \quad (3.6b)$$

Equations 3.6a and 3.6b describe the alternative hypothesis, which accounts for both divergence and club convergence. The test is operationalized through the ‘log-t’ regression:

$$\log(H_1/H_t) - 2 \log L(t) = \hat{\alpha} + \hat{\beta} \log t + u_t, \text{ for } t = [rT], [rT] + 1, \dots, T, \text{ with } r > 0. \quad (3.7)$$

In Equation 3.7, r represents the initial fraction of the data used to start the regression, effectively discarding the first portion of the sample to ensure results are not driven by initial conditions. For sample sizes where $T \leq 50$, Phillips, and Sul (2007) suggest setting $r = 0.3$. Under this specification, a one-sided t-test is employed to assess convergence, where the null hypothesis is rejected if the t-statistic satisfies $\hat{t} < -1.65$.

If the log-t test rejects general convergence for the entire sample, the clustering algorithm developed by Phillips, and Sul (2007) serves to identify convergent and divergent clubs. A primary advantage of this framework is its capacity to detect multiple convergence clusters within a subset, even when the broader panel exhibits divergence. Building upon this, Phillips, and Sul (2009), Schnurbus, Haupt, and Meier (2017), Du (2017), and Sichea, and Pizzuto (2019) refined a data-driven procedure to detect these multiple clubs through the following iterative steps: i) Order the panel members based on the final observation in the sample; ii) Identify a core group of entities that yields the highest convergence t-statistic, such that $t_{\hat{\beta},k} > 1.65$; iii) Sequentially add members to the core group as long as the t-statistic exceeds a

predetermined critical value $t_{\hat{\beta} > c^*}$; iv) Form a subsequent convergence club if the null hypothesis is not rejected for the remaining units. If rejected, repeat steps 1-3 to identify further subgroups or confirm divergent behavior.

3.5 Results

3.5.1 Unit Root Tests and GMM Estimations

Assessing the stationarity of the time series at level is a fundamental step for our econometric modeling. To ensure robustness, we performed a comprehensive battery of unit root tests, including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS). As reported in Table 3.2, the results consistently indicate that all variables are stationary at level. This finding confirms the suitability of the data for subsequent analysis, providing a solid foundation to investigate the persistence of inflation in the 11 Brazilian cities and metropolitan areas.

Table 3.2 – Unit Root Test - CPI Inflation

Test	ADF	PP	ADF-GLS	KPSS	Integration
Variables	t statistic	t statistic	t statistic	LM statistic	Order
CPI - Brazil	-9.198*	-9.097*	-0.548	0.084	I(0)
CPI - Rio de Janeiro	-10.552*	-10.465*	-0.186	0.135	I(0)
CPI - São Paulo	-9.905*	-9.978*	-0.823	0.067	I(0)
CPI - Belo Horizonte	-11.276*	-11.356*	-0.449	0.264	I(0)
CPI - Brasília	-13.500*	-13.403*	-0.434	0.213	I(0)
CPI - Fortaleza	-10.418*	-10.347*	-1.023	0.071	I(0)
CPI - Recife	-11.036*	-10.997*	-0.502	0.136	I(0)
CPI - Salvador	-13.384*	-13.616*	-0.482	0.084	I(0)
CPI - Belém	-10.754*	-10.679*	-0.623	0.232	I(0)
CPI - Goiânia	-11.375*	-11.465*	-0.613	0.122	I(0)
CPI - Curitiba	-10.237*	-10.356*	-1.618	0.060	I(0)
CPI - Porto Alegre	-10.577*	-10.555*	-0.312	0.120	I(0)
Inflation Expectations	-3.877*	-6.414*	-0.789	0.353	I(0)
Real Exch. Rate (Δe_t)	-12.562*	-12.618*	-2.369*	0.453	I(0)
Economic Activity (y_t)	-6.629*	-5.589*	-5.871*	0.022	I(0)

Note: * statistical significance at 5%. ADF, PP, DF-GLS: H_0 = unit root; KPSS: H_0 = stationarity. CPI for Brazil and regions.

Table 3.3 presents the benchmark GMM estimations for the regional Phillips Curves across the 11 metropolitan areas, with the J-test results confirming the validity of the instrumental variables. Inflation persistence (inertia) is statistically significant at the 5% level in all estimated models, with coefficients ranging from 0.116 (Brasília) to 0.392 (Fortaleza).

These results provide the first indication of regional disparities in inflation persistence across Brazil, while also confirming mean-reverting behavior. Regarding the other determinants, CPI inflation expectations are statistically significant in 5 out of the 12 estimations, while the exchange rate coefficient is significant in 9 cases. In contrast, the output gap parameter is significant in only one estimation. These preliminary findings highlight the need for a more

in-depth investigation through time-varying parameter models to further explore the evolving nature of regional inflation dynamics in the country.

Table 3.3 – Regional CPI Inflation (% month) - Descriptive Statistics and Regional Weights

Dependent	Independent Variables (coefficients and standard errors)					Stat. J (p-value)
Variables	Intercept	$\pi_{t-1}^{\text{Brazil}}$	$E_t \pi_{t+1}$	Δe_{t-4}	y_t	
CPI - Brazil	-0.127 (0.303)	0.370* (0.120)	1.042 (0.868)	-1.631* (0.507)	0.007 (0.007)	2.071 (0.558)
CPI - Rio de Janeiro	0.099 (0.070)	0.296* (0.070)	0.553* (0.184)	-2.109* (0.614)	2.143* (0.753)	6.090 (0.107)
CPI - São Paulo	0.102 (0.073)	0.453* (0.065)	0.365 (0.193)	-1.448* (0.383)	0.779 (0.714)	1.642 (0.440)
CPI - Belo Horizonte	0.010 (0.466)	0.248* (0.097)	0.858 (1.213)	-1.741* (0.792)	1.037 (0.982)	2.443 (0.118)
CPI - Brasília	0.138 (0.123)	0.116* (0.058)	0.655* (0.297)	-1.885* (0.803)	-0.147 (2.028)	1.648 (0.439)
CPI - Fortaleza	0.409 (0.371)	0.392* (0.080)	-0.324 (0.985)	-0.973 (0.703)	0.758 (1.230)	3.666 (0.300)
CPI - Recife	-0.269 (0.312)	0.275* (0.087)	1.530 (0.833)	-1.481* (0.655)	-0.166 (1.205)	1.681 (0.641)
CPI - Salvador	0.166 (0.108)	0.130* (0.058)	0.550 (0.291)	-1.737* (0.801)	1.810 (1.035)	2.480 (0.477)
CPI - Belém	0.293 (0.392)	0.381* (0.077)	0.010 (1.032)	-1.006 (0.610)	0.393 (0.975)	1.390 (0.708)
CPI - Goiânia	-0.034 (0.118)	0.199* (0.063)	0.994* (0.294)	-1.859 (0.974)	1.697 (1.251)	1.763 (0.414)
CPI - Curitiba	-0.018 (0.125)	0.358* (0.071)	0.768* (0.306)	-2.305* (0.650)	0.583 (1.193)	3.946 (0.139)
CPI - Porto Alegre	0.049 (0.122)	0.293* (0.082)	0.678* (0.339)	-1.975* (0.647)	1.582 (0.965)	1.095 (0.778)

Note: * Statistical significance at 5%. H_0 (J Test): Instruments are valid. CPI for Brazil and 12 regions.

3.5.2 Time-Varying Parameter Results

To evaluate our claim that regional inflation in Brazil exhibits a dual nature, we first investigate the persistence of regional inflation. This stage involves applying the Kalman filter to estimate Time-Varying Parameters (TVPs) for each regional hybrid Phillips Curve, as specified in Equation 3.1. To initialize the state-space model, we use the coefficients and standard errors derived from benchmark GMM estimations, which define the initial magnitude and variance of the state vectors. Following standard practice, confidence intervals for these evolving parameters are constructed using twice the root mean square error (RMSE), providing a robust measure of statistical uncertainty across the sample period.

While Equation 3.1 encompasses multiple determinants, our analysis focuses primarily on the dynamics of the inflation persistence coefficient, which is the central object of this study. Consequently, Figure 3.2 presents the evolution of this specific parameter across the metropolitan areas; other estimated TVP coefficients are omitted to focus the discussion on the central hypothesis but remain available upon request.

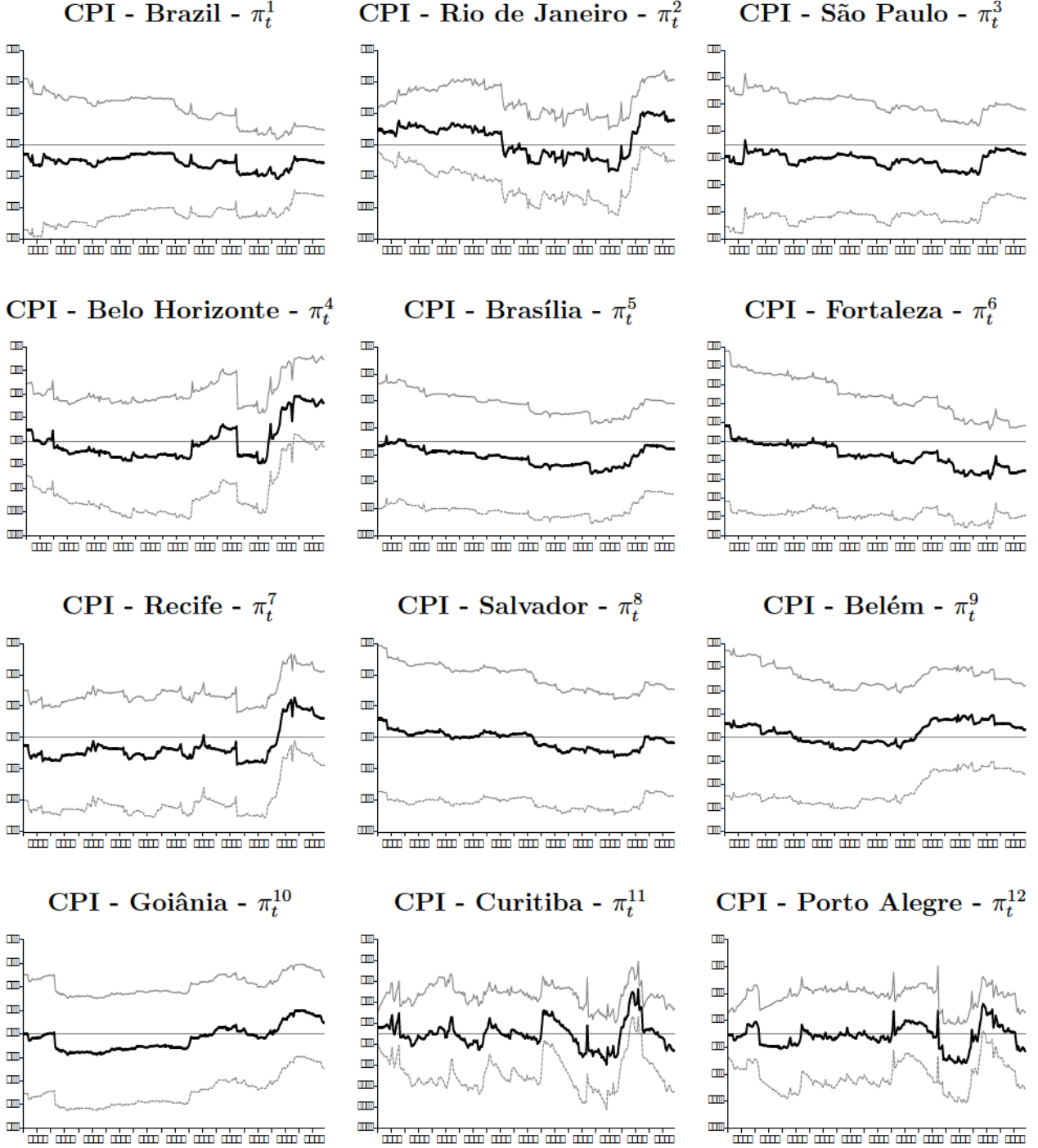
Figure 3.2 illustrates the Time-Varying Parameters for regional inflation persistence, revealing a clear dichotomy in subnational price dynamics. While the aggregate IPCA persistence

oscillates stably around 0.4, regional trajectories diverge significantly from this benchmark. At one end of the spectrum, Salvador and Fortaleza exhibit a gradual decline in inflationary inertia, differing markedly from the national CPI behavior. This trend corroborates previous studies, such as those by Gomes da Silva, and Vieira (2013) and BCB (2017), which highlight the structural heterogeneity of regional inflation. Similarly, Brasília and Goiânia show only subtle reactions to systemic shocks, maintaining a low-persistence profile (Gomes da Silva, and Fishlow, 2021). In contrast, São Paulo maintains a higher and remarkably steady plateau near 0.5, likely reflecting the price stickiness and high indexation inherent to its dominant services sector (Minella et al., 2003). Meanwhile, Rio de Janeiro, Belo Horizonte, and Recife exhibit more moderate, though visible, pandemic-induced upward shifts in their persistence parameters.

The most striking evidence of parameter instability emerges from metropolitan areas in Southern Brazil. Curitiba and Porto Alegre, for instance, experienced significant spikes in inflationary persistence during the COVID-19 pandemic, followed by subsequent corrections. This pattern aligns with reports from the Central Bank of Brazil (BCB, 2021; BCB, 2024), which highlight that while the South faced severe supply-side disruptions, it also recorded the country’s lowest inflation rate in 2024 due to the rapid normalization of food and industrial prices. In the specific case of Curitiba, Bittencourt, and S. M. Silva (2015) argues that inflation is highly sensitive to exchange rate volatility and commodity shocks given the city’s industrial density and open-economy traits. Such unique exposure explains why global supply shocks triggered sharp, albeit transient, increases in inflationary inertia in the South. Furthermore, these findings provide robust evidence of aggregation bias, as national headline indices often mask such localized shifts (Bastos, and N. G. d. Silva, 2010).

In summary, our TVP-Phillips curve estimations provide robust empirical support for the first proposition of our central claim, demonstrating that inflation persistence in Brazil is not a static phenomenon. By capturing significant variations through state-space models, these estimations confirm that regional inflation rates are structurally heterogeneous and endogenous to systemic shocks. Consequently, these findings suggest that national aggregate measures may conceal substantial localized inertia, highlighting an inherent aggregation bias in broader inflation persistence metrics.

Figure 3.2 – Regional Inflation Persistence (π_t^L , Kalman Filter Estimation)



3.5.3 Club Convergence Results

Building on this evidence of structural heterogeneity, the following section evaluates the second proposition of our ‘dual-nature’ claim: the existence of significant disparities in regional inflation convergence. While regional aggregate inflation may diverge across locations, convergence is more likely to emerge at the sectoral level. By analyzing our Club Convergence results, we gain a deeper understanding of how the dual nature of Brazilian inflation manifests across distinct economic cycles and geographic clusters.

Regarding the regional headline CPI-IPCA, Table 3.4 shows that global convergence

is rejected, indicating that inflation across the 11 Brazilian cities does not gravitate toward a single steady state. However, while overall equilibrium is absent, the transition paths suggest the existence of local convergence clubs. In this context, the null hypothesis of convergence is not rejected for four specific clubs. Notably, these clubs exhibit negative coefficients, which Phillips, and Sul (2009) and G. M. Caporale, You, and L. Chen (2019) characterize as a ‘transitional divergence and turn-around phase’. Alternatively, Mendez (2020) interprets these cases as ‘local weak convergence.’ Both perspectives imply that while the dynamic process falls within the non-rejection region, the negative sign indicates a period of potential divergence followed by a transition that may or may not lead to strong convergence. These four groups comprise: (i) Club 1: Rio de Janeiro and Belém; (ii) Club 2: Goiânia and Curitiba; (iii) Club 3: São Paulo and Fortaleza; and (iv) Club 4: Brasília, Recife, Salvador, and Porto Alegre. Belo Horizonte stands out as the only city exhibiting no convergence with any other location.

The evidence for the headline index, characterized by no global convergence and four cases of weak local convergence, contrasts significantly with the results for individual CPI-IPCA components. When analyzing the eleven sectoral inflation rates, we find evidence of global convergence for ‘Household Items’ and ‘Transportation’, as their coefficients are positive and the null hypothesis is not rejected ($\hat{\beta} > -1.65$). This suggests that price disparities in these sectors are diminishing over time, leading toward a common steady state. Furthermore, ‘Global Weak Convergence’ is detected for ‘Communication’, ‘Food and Beverage’, and ‘Food at Home’. In these cases, despite the negative coefficients, the results remain within the null hypothesis region, signaling a transitional phase where regional disparities are gradually aligning toward a common trend.

The remaining components are characterized primarily by local weak convergence clubs. In the ‘Housing’ sector, three such clubs emerge: Club 1 (Recife and Curitiba), Club 3 (Fortaleza and Salvador), and Club 4 (Goiânia and Porto Alegre). Significantly, Club 2 (Rio de Janeiro, São Paulo, and Belém) represents the only instance of ‘strong’ local club convergence found in this study, evidenced by its positive coefficient. Finally, Belo Horizonte and Brasília remain isolated in several components, reinforcing their unique and divergent inflationary dynamics.

As noted by Phillips, and Sul (2009) and Mendez (2020), the initial algorithm may over-predict the number of clubs, necessitating sequential merging tests. In the Housing component, the merger of Clubs 2 and 3 cannot be rejected; although the resulting coefficient is negative, it suggests weak convergence (transitional divergence). Consequently, regional Housing inflation is characterized by three distinct groups: Club 1, the merged Club (2+3), and Club 4.

For the Clothing component, our results initially identify two weak convergence clubs: Club 1 (Belo Horizonte, Salvador, and Curitiba) and Club 2 (Rio de Janeiro, Brasília, Recife, Goiânia, and Porto Alegre), while São Paulo and Fortaleza exhibit divergent dynamics. However, the merging test for Clubs 1 and 2 is not rejected, indicating that the sector can be effectively represented by a single merged convergence club (1+2).

The Health and Personal Care sector displays three weak convergence clubs: Club 1

(Brasília and Goiânia), Club 2 (Belo Horizonte and Porto Alegre), and Club 3 (Recife and Salvador). Conversely, Rio de Janeiro, São Paulo, Fortaleza, Belém, and Curitiba remain outside these clusters, suggesting idiosyncratic inflationary paths. In the Personal Expenses component, two weak convergence clubs emerge: Club 1, comprising the major metropolitan centers of Rio de Janeiro, São Paulo, Brasília, and Fortaleza, and Club 2, which includes the remaining cities such as Porto Alegre, Belém, and Curitiba.

Analysis of the Education component reveals three initial clubs. Similar to previous cases, the merger of Club 1 (major capitals and Belém) and Club 2 (Belo Horizonte, Brasília, and Recife) is statistically supported. Thus, Education inflation is defined by two broader groups: the merged Club (1+2) and Club 3 (Goiânia and Curitiba). Finally, the Food Away from Home component is characterized by three weak convergence clubs: Club 1 (Rio de Janeiro, Belo Horizonte, Goiânia, and Porto Alegre), Club 2 (Recife and Belém), and Club 3 (Brasília and Fortaleza). In this sector, São Paulo, Salvador, and Curitiba do not converge with any other city, reinforcing the evidence of structural heterogeneity in regional food services.

Our findings of local convergence clubs and global weak convergence in specific sectors align with recent evidence from continuous wavelet transform (CWT) analyses, which reveal that regional inflation synchronization in Brazil is highly scale-dependent. While studies such as Lucena (2025) identify strong long-run synchronization (4-8 years) between regional and national indices, our results qualify this relationship by showing that such co-movements do not necessarily imply a single global steady state. Instead, the ‘transitional divergence and turn-around phase’ identified in our city-level clubs explains the lower synchronization observed in shorter frequencies (6-12 months), with integrated sectors like ‘Household Items’ and ‘Transportation’ driving long-term convergence, whereas idiosyncratic shocks in ‘Food and Beverage’ underpin regional asymmetries.

We can also contextualize these results by comparing them to those observed in other emerging and developed economies. For instance, Christou, Cunado, and Gupta (2019) and Aginta (2020) identified fewer convergence clubs in specific sectors, such as housing and education, relative to the aggregate index in the United States and Indonesia, respectively. Similarly, Fan et al. (2023) found limited evidence of global convergence in food price inflation, which is consistent with our findings of sectoral fragmentation. In contrast, Cuestas, L. A. Gil-Alana, and Taylor (2016) reported broader convergence across Central and Eastern European countries, suggesting that deeper institutional integration may override the localized inertia observed in the Brazilian case.

Therefore, based on the Club Convergence results in Table 3.4, we provide robust empirical support for the second proposition of our central claim regarding regional inflation convergence. Considering Brazil’s continental dimensions and pronounced regional disparities in income and development, there is only weak evidence that regional inflation converges to a uniform steady state. The absence of global convergence likely reflects the heterogenous economic growth and socio-economic trajectories across Brazilian metropolitan areas.

Table 3.4 – Club Convergence Results (Club Merging) for Groups and Subgroups

Sample	Cities	$\hat{\beta}$ coeff	SE	t-Stat
Global Convergence (Headline)	All cities	-1.217*	0.469	-2.597
Club 1	Rio, Belém	-0.989 ^T	0.799	-1.237
Club 2	Goiânia, Curitiba	-1.208 ^T	0.743	-1.625
Club 3	São Paulo, Fortaleza	-0.800 ^T	0.657	-1.219
Club 4	Brasília, Recife, Salvador, Porto Alegre	-1.081 ^T	0.696	-1.553
Global Convergence (Household items)	All cities	1.628	0.860	1.893
Global Convergence (Transportation)	All cities	0.627	0.651	0.963
Global Convergence (Communication)	All cities	-0.001 ^T	0.638	-0.002
Global Convergence (Food and Beverage)	All cities	-0.901 ^T	0.560	-1.610
Global Convergence (Food at home)	All cities	-0.388 ^T	0.621	-0.625
Global Convergence (Housing)	All cities	-1.409*	0.436	-3.233
Club 1	Salvador, Curitiba	-1.483 ^T	0.941	-1.576
Club 2	Rio, São Paulo, Belém	0.028	0.552	0.051
Club 3	Fortaleza, Recife	-0.741 ^T	0.684	-1.082
Club 4	Goiânia, Porto Alegre	-1.135 ^T	0.814	-1.394
Club Merging Test (Club 2 + 3)		-0.521 ^T	0.573	-0.908
Global Convergence (Clothing)	All cities	-1.607*	0.653	-2.461
Club 1	Belo Horizonte, Salvador, Curitiba	-0.698 ^T	0.587	-1.188
Club 2	Rio, Brasília, Recife, Goiânia, Porto Alegre	-1.227 ^T	0.796	-1.541
Club Merging Test (Club 1 + 2)		-0.846 ^T	0.627	-1.350
Global Convergence (Health, Personal Care)	All cities	-1.564*	0.347	-4.502
Club 1	Brasília, Goiânia	-1.161 ^T	0.724	-1.604
Club 2	Belo Horizonte, Porto Alegre	-0.409 ^T	0.600	-0.681
Club 3	Recife, Salvador	-0.912 ^T	0.582	-1.569
Global Convergence (Personal Expense)	All cities	-0.814*	0.481	-1.694
Club 1	Rio, São Paulo, Brasília, Fortaleza, Recife, Salvador, Goiânia, Porto Alegre	-0.757 ^T	0.471	-1.608
Club 2	Belo Horizonte, Belém, Curitiba	-0.503 ^T	0.585	-0.861
Global Convergence (Education)	All cities	-0.776*	0.459	-1.690
Club 1	Rio, São Paulo, Fortaleza, Salvador, Belém, Porto Alegre	-0.162 ^T	0.527	-0.306
Club 2	Belo Horizonte, Brasília, Recife	-0.813 ^T	0.509	-1.595
Club 3	Goiânia, Curitiba	-0.487 ^T	0.823	-0.592
Club Merging Test (Club 1 + 2)		-0.791 ^T	0.480	-1.647
Global Convergence (Food away from home)	All cities	-1.889*	0.580	-3.260
Club 1	Rio, Belo horizonte, Goiânia, Porto Alegre	-0.605 ^T	0.582	-1.040
Club 2	Recife, Belém	-0.898 ^T	0.650	-1.382
Club 3	Brasília, Fortaleza	-0.661 ^T	0.635	-1.041

Note: * indicates rejection of the null hypothesis of convergence and club merging at the 5% significance level. ^T indicates transitional divergence and turn-around phase. SE is the standard error.

However, when the analysis shifts from headline inflation to its eleven disaggregated components, a more nuanced pattern emerges. We find strong global convergence in household items and transportation, whereas sectoral inflation for communication, food and beverage, and food at home is characterized by a ‘transitional divergence and turn-around phase’ (Phillips, and Sul, 2009).

This study also reveals that the speed of convergence varies significantly across groups and sub-groups. This variation in transition dynamics across sectors may explain the lack of aggregate convergence at the national level, as it depends on sectoral weight in household budgets and their respective adjustment speeds. Furthermore, the results suggest that certain

cities have leveraged their infrastructure and resources to ‘catch up’ with more economically advanced centers. Such localized dynamics reinforce our central claim: national aggregate measures of inflation persistence may conceal substantial localized inertia, stressing the presence of a significant aggregation bias.

3.6 Conclusion

This article investigated the inflation persistence phenomenon and price convergence dynamics across 11 Brazilian metropolitan areas from January 2003 to November 2024. It aimed to test the central hypothesis that Brazilian inflation exhibited a dual nature, where regional persistence was structurally heterogeneous and endogenous to systemic shocks, while long-run convergence was driven by integrated sectoral components rather than aggregate headline figures. The methodology involved applying Time-Varying Parameters to analyze regional inflation persistence and the Convergence-by-Clubs approach for group investigation. This dual-track objective sought to fill a gap in the Brazilian literature by providing a detailed and comprehensive view of regional inflationary similarities and disparities.

The combination of these methodologies yielded a robust analysis of regional dynamics. The results revealed significant heterogeneity in persistence; while São Paulo, Salvador, Belém, and Brasília exhibited low persistence, Curitiba showed high price inertia. Specifically, Salvador (Northeast) displayed very low inertia, indicating short-memory inflation, whereas Curitiba (South) was characterized by long-memory inflation. This disparity confirms the structural heterogeneity of inflationary memory across the country. During the COVID-19 pandemic, Recife, Belo Horizonte, Rio de Janeiro, and Curitiba experienced episodes of ‘inertial migration’, a sharp increase in persistence. This phenomenon indicates that regional inertia is indeed endogenous to systemic shocks, as price settings were strongly influenced by supply chain disruptions followed by demand-side pressures.

Regarding club convergence, no evidence of overall equilibrium was found among the 11 regional headline series. Instead, only clubs characterized by a transitional divergence and turn-around phase emerged. However, disaggregating the headline IPCA into 11 components uncovered global convergence in Household Items and Transportation. While results for Communication and Food categories also showed no rejection of the convergence null hypothesis, their negative coefficients define them as being in a transitional or weaker convergence phase.

Collectively, these findings validate the study’s central claim: while aggregate headline inflation remains divergent, price stability in Brazil is a fragmented process where sectoral-led convergence in integrated markets serves as the primary engine for national price integration. Consequently, the results demonstrate that analyzing disaggregated data uncovers critical aspects of price convergence obscured by headline figures, highlighting a significant aggregation bias. This study emphasizes that inflation persistence is as much a regional phenomenon as a national one, as idiosyncratic behaviors within a country of continental dimensions lead to partial or sectoral convergence. The presence of convergence clubs suggests that monetary policies

and regional development strategies must account for these specificities to be effective.

Further research is needed to explore the socio-economic determinants behind these regional patterns of inertia. Moreover, given the prevalence of weak convergence detected, future investigations could deepen this analysis by employing the specific weak σ -convergence methodology proposed by Kong, Phillips, and Sul (2019).

The empirical evidence established in this study provides a concrete operational diagnostic to bridge the gap between regional inflation dynamics and monetary policy practice. Our findings directly contribute to Sustainable Development Goals (SDG) 8 - Decent Work and Economic Growth, particularly Target 8.5, by identifying regional disparities and convergence patterns that inform targeted inflation control. By fostering economic stability, these insights support sustainable growth across Brazilian regions. Consequently, the Central Bank should move away from 'one-size-fits-all' strategies toward differentiated policy responses and communications. While the Central Bank publishes regional reports, their annual frequency and significant time lag hinder agile decision-making. Modernizing these communication tools is essential to address the varied inflation persistence found across metropolitan areas.

Furthermore, this research relates to SDG 10 - Reduced Inequalities, especially Target 10.2, by highlighting the importance of addressing diverse regional economic realities to ensure no region is left behind. A critical step toward this goal is the geographical expansion of Brazil's official inflation measurement. Given the country's continental dimensions and pronounced regional disparities, integrating more regions and interior cities into the official IPCA calculation, managed by the Brazilian Institute of Geography and Statistics (IBGE), is imperative. Currently, the concentration of data in major cities and metropolitan areas may fail to capture the idiosyncratic inflationary pressures of expanding agricultural frontiers and emerging industrial hubs, further exacerbating the aggregation bias. Expanding the IBGE's survey coverage would provide a more representative national diagnostic, essential for inclusive policy-making.

Since sectors such as 'Food and Beverages' exhibit weak convergence, targeted micro-economic interventions are vital to stabilize regional prices. Current policies, such as Conab's strategic food reserves and the National Basic Food Basket tax harmonization, align with this goal. However, these instruments often face criticism due to limited operational scale and infrastructure bottlenecks, the so-called 'Custo Brasil.' While the Food Acquisition Program (PAA) strengthens local supply chains, a more robust, regionally coordinated logistics strategy is required to ensure that temporary price spikes do not consolidate into permanent inflationary trends.

Central to this challenge is the structural state of Brazil's transportation infrastructure. Despite marginal improvements in recent years, the system remains constrained by quality gaps and an over-reliance on road transport. The persistent lack of extensive railway and waterway networks hinders cost-effective long-haul freight and leaves regional markets vulnerable to supply shocks. Addressing these structural bottlenecks is essential to reduce transaction costs and effectively integrate divergent markets, helping to mitigate the localized inertia that currently

fuels the aggregation bias in national inflation figures.

Finally, development banks, such as the Brazilian Development Bank (BNDES), the Northeast Bank of Brazil (BNB), and the Bank of Amazon (BASA), should incorporate inflation persistence metrics into their strategic credit allocation. To act as a structural disinflationary force, financing in high inflation inertia regions should shift toward investments that enhance supply capacity. By tailoring credit conditions to the specific dynamics of established ‘Convergence Clubs’, rather than adhering to rigid geopolitical borders, policymakers can ensure that regional growth does not trigger localized inflationary pressures that diverge from the national equilibrium.

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Appendix A. Phillips Curve Figures - CPI Regional

Figure 3.3 – Regional Inflation Intercept (π_t^L , Kalman Filter Estimation)

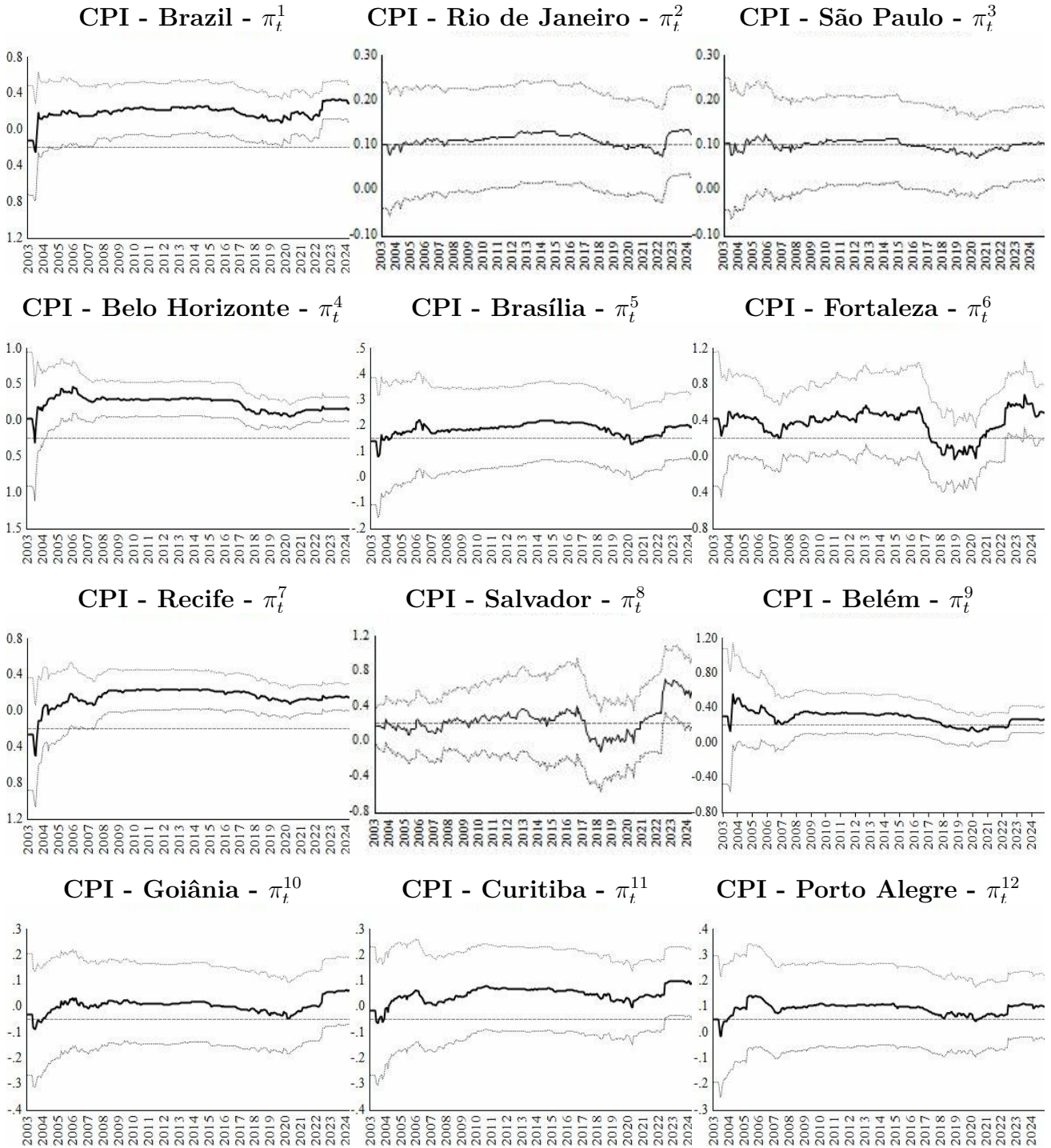


Figure 3.4 – Regional Inflation Expectations (π_t^L , Kalman Filter Estimation)

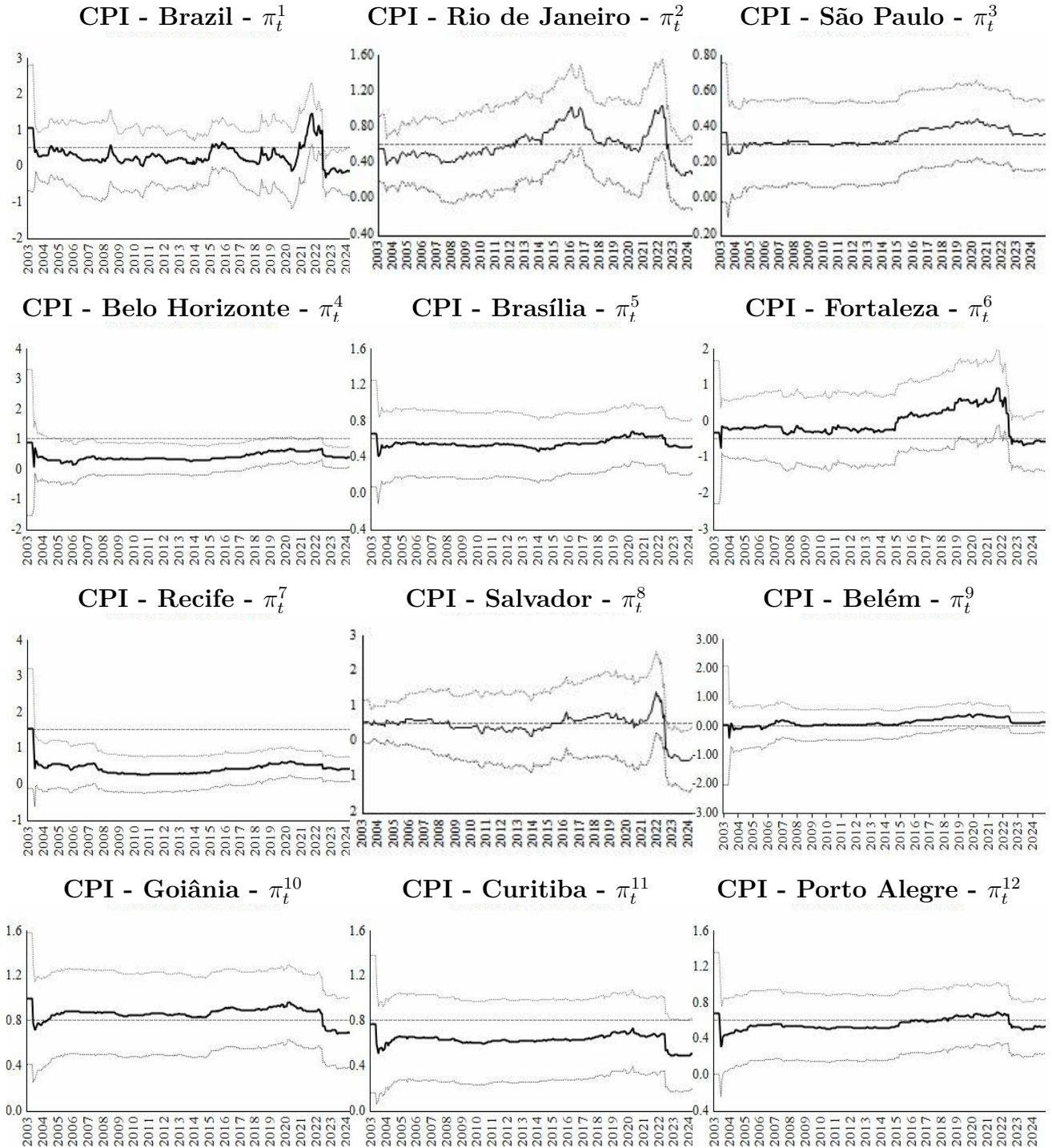


Figure 3.5 – Regional Exchange Rate Pass-Through (π_t^L , Kalman Filter Estimation)

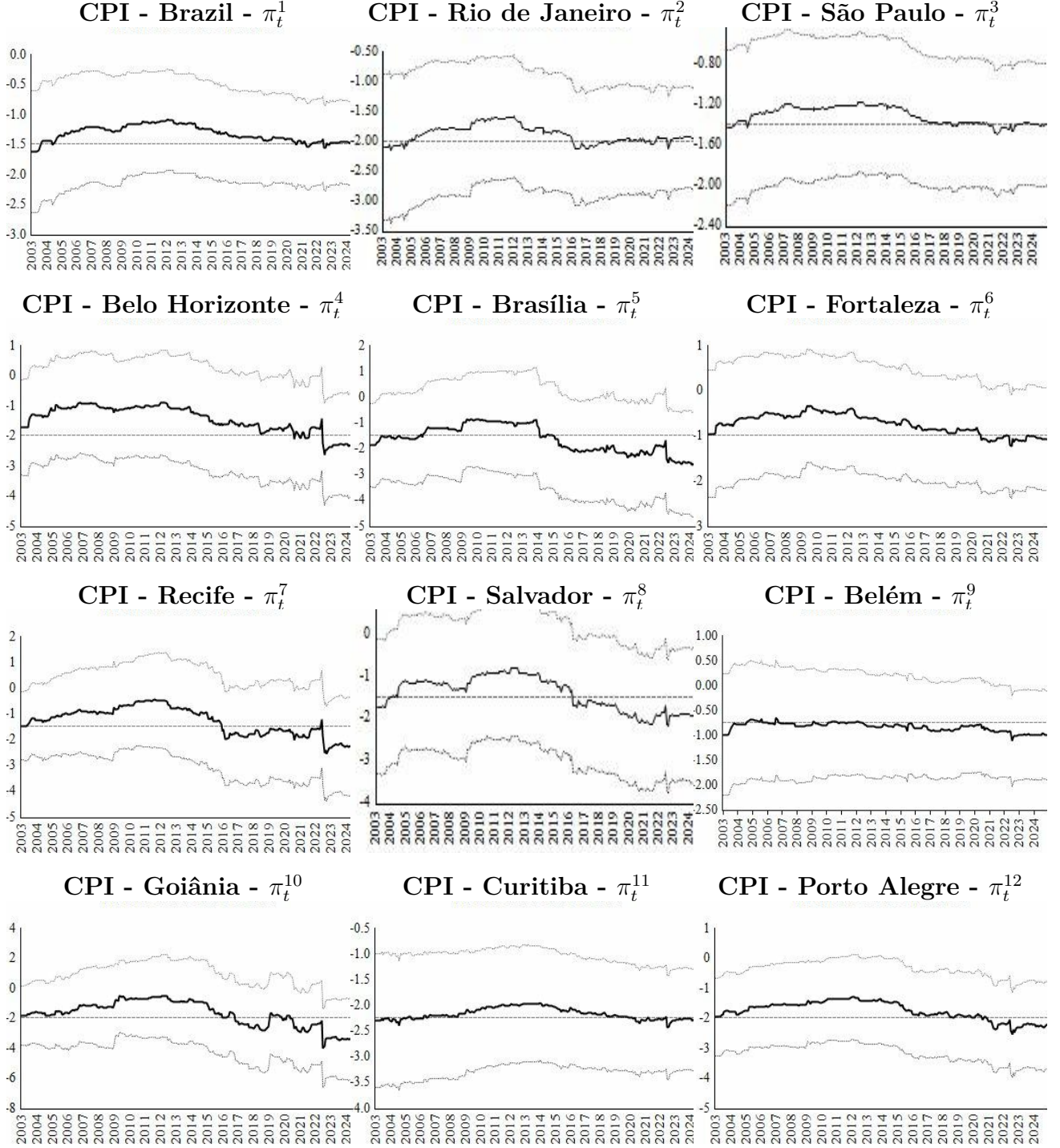
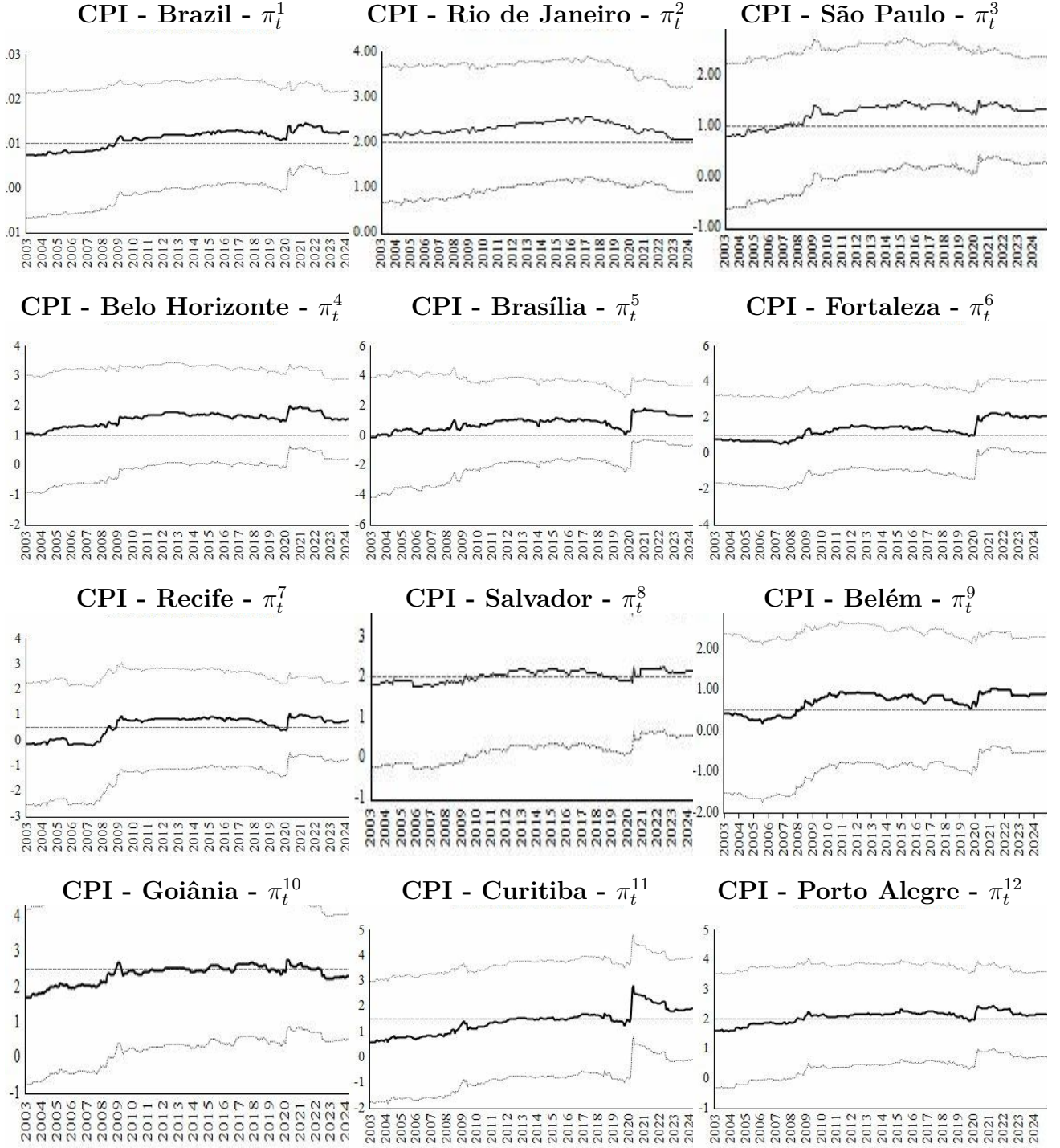


Figure 3.6 – Regional Output Gap (π_t^L , Kalman Filter Estimation)



4 INFLATION INEQUALITY ACROSS HOUSEHOLD INCOME GROUPS IN BRAZIL: PERSISTENCE, TREND AND VOLATILITY

Abstract

This article investigates inflation inequality across four income strata in Brazil (very low, low, middle, and high income) from July 2006 to April 2025, using the Headline IPCA as a benchmark. We test the hypothesis that inflation dynamics and transmission mechanisms are structurally unequal and disproportionately affect lower-income households. The methodology employs a Univariate Unobserved Components model with Stochastic Volatility and Outlier Adjustment (UCSVO) to analyze trend and volatility, followed by a Time-Varying Parameter (TVP) Phillips Curve to assess persistence and macroeconomic sensitivity. Results indicate that: (i) trend inflation is consistently higher and more volatile among lower-income groups; (ii) inflation outliers are more frequent and intense for these cohorts; (iii) inflation persistence ranges from 0.20 to 0.40, being particularly unstable at the extremes of the income distribution; and (iv) transmission mechanisms are highly asymmetric, with inflation expectations being significant exclusively for the high-income group, while the output gap has influenced lower-income strata since 2008, well before its 2020 impact on the headline IPCA. This indicates that monetary policy targets may be structurally delayed for the most vulnerable, demonstrating that relying solely on aggregate indices introduces systemic policy lags. Ultimately, these findings reveal that a unified monetary intervention can inadvertently deepen socioeconomic divides by failing to address the highly inertial and exposed price dynamics of lower-income strata.

Keywords: IPCA; Income Groups; Stochastic Volatility; UCSVO.

JEL Classification: C32; D31; E31.

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4.1 Introduction

Since the 1994 Real Plan, Brazil’s macroeconomic stabilization has been anchored by an inflation-targeting regime that adopts the Extended National Consumer Price Index (IPCA) as its official target benchmark. Although the Headline IPCA reflects average household inflation, its aggregated nature masks significant heterogeneities across income groups, obscuring how price shocks affect a society marked by deep structural inequalities. Low-income households allocate a larger share of their budget to volatile and persistent essential items, such as food and energy, while higher-income groups maintain more diversified baskets with lower exposure to price disturbances. This divergence creates disparate inflationary experiences that further exacerbate socio-economic divides.

Therefore, understanding these asymmetries is a structural necessity for central banking, rather than a mere distributional exercise. If policymakers rely only on aggregated indices, they risk committing systematic policy errors by miscalculating the timing and magnitude of monetary interventions. A “one-size-fits-all” approach not only ignores how distinct income strata respond to shocks, but can inadvertently cause tightening or easing cycles to amplify the economic burdens of the most vulnerable while failing to anchor expectations among the wealthy. This paper matters precisely because it untangles these hidden operational frictions.

In light of these disparities, this article addresses the following question: to what extent do inflation dynamics and macroeconomic transmission mechanisms differ across income strata in Brazil? To address this issue, we investigate four strata (very low, low, middle, and high income) from July 2006 to April 2025, using the Headline IPCA as a benchmark. The central hypothesis is that inflation dynamics in Brazil are structurally unequal, with lower-income households facing a disproportionately more intense, volatile, and persistent inflationary process, while transmission mechanisms operate heterogeneously across groups. Methodologically, the study employs two econometric techniques: a Univariate Unobserved Components Model with Stochastic Volatility and Outlier Adjustment (UCSVO), to analyze trend and volatility dynamics, and a Time-Varying Parameter (TVP) Phillips Curve, to evaluate the influence of macroeconomic variables and inflation inertia. In addition to group-specific IPCA series, this second analysis incorporates inflation expectations, the Central Bank’s Economic Activity Index (IBC-Br) as a proxy for the output gap, and the real effective exchange rate.

Although previous studies have documented consumption discrepancies across income classes, literature often treats inflation dynamics as static or fails to simultaneously account for stochastic volatility, parameter variations, and recent global shocks in emerging economies. This study bridges this gap and contributes to the existing literature in three ways. First, it provides a comprehensive decomposition of inflation dynamics using a UCSVO model to capture stochastic volatility and outliers across income strata. Second, by employing a TVP Phillips Curve, it identifies time-varying asymmetries in macroeconomic transmission, particularly concerning inflation inertia and expectations. Finally, it offers updated empirical evidence on the regressive nature of inflation in a major emerging economy, covering recent global shocks up to 2025.

The empirical findings confirm a regressive bias in Brazilian inflation by income groups, highlighting the increased vulnerability of low-income households to both persistent and abrupt price shocks and revealing a structurally unequal inflation burden across income strata. Univariate estimates provide evidence of structural heterogeneity in price dynamics between income groups. Trend inflation is consistently higher and more volatile among very low- and low-income households, with high transitory and permanent volatility, especially between 2006 and 2016, reflecting persistent exposure to essential goods. In these groups, inflation uncertainty also exerts a stronger and more persistent effect compared to higher strata. Although transitory volatility declines after 2017, falling below the IPCA, it remains persistently elevated for these groups over time. In contrast, high-income households show increased transitory volatility from 2018 onward, reflecting greater sensitivity to volatile items, particularly following the COVID-19 pandemic shock. Inflation outliers occur more frequently and with greater magnitude in lower-income groups, decreasing in frequency and size as income rises.

In the multivariate investigation, the TVP Phillips Curve, estimated via the Kalman Filter, reveals substantial variation in inflation persistence across income groups compared to the Headline IPCA. Lagged inflation, our main variable of interest and proxy for inertia, is statistically significant for all strata except the high-income group during specific intervals. While IPCA persistence remains moderate and relatively stable, instability is more pronounced at inflation rates on the extremes of the income distribution (very low- and high-income groups). Regarding the control variables, the results show heterogeneous inflation dynamics and distinct macroeconomic transmission mechanisms across income strata, with the inflation expectations channel showing significance mainly for the high-income group.

In summary, these results demonstrate that inflation in Brazil is structurally unequal, characterized by inertia and abrupt shocks for the poor, and more forward-looking behavior among the wealthy. Such statistical discrepancies translate into profound economic asymmetries: while high-income households can effectively hedge against inflation through forward-looking expectations, lower-income strata remain trapped by inertia and delayed policy responses. Therefore, our findings bridge the literature on consumption discrepancies with the broader debate on macroeconomic transmission lags. Ultimately, this evidence highlights the challenges of using the Headline IPCA as the only metric for economic policy, rendering it necessary for policymakers to adopt income-disaggregated indicators to prevent monetary policy from inadvertently exacerbating socioeconomic divides.

The remainder of this article is organized as follows: Section 2 reviews the literature and Section 3 details the data and inflation characteristics. Section 4 describes the econometric methodologies. Section 5 discusses the empirical findings and Section 6 concludes.

4.2 Literature

Inflation inequality arises because consumption baskets differ across socio-economic strata. While lower-income households are disproportionately exposed to inelastic essential

goods, wealthier families enjoy diversified spending that cushions price shocks. Pioneering this distributive analysis, Michael (1979) and Hagemann (1982) provided the first quantitative evidence for the U.S., proving that aggregate price indices mask substantial variation across subgroups. However, these early empirical efforts were limited by highly aggregated consumption data.

Subsequent studies leveraging higher-frequency data validated these findings. Hobijn, and Lagakos (2005) confirmed significant inflation variation across U.S. households from 1984 to 2004, showing that low-income groups faced higher inflation due to volatile essential goods like fuel and healthcare, though these shocks exhibited low persistence. Similarly, Kaplan, and Schulhofer-Wohl (2017) analyzed 50,000 U.S. households between 2004 and 2013, reinforcing this regressive nature by demonstrating that lower-income families consistently experience higher average inflation across time and locations.

Lee (2022) showed that Black households in the U.S. experienced higher and more volatile inflation than White households (2004–2020), with two-thirds of the variance driven by price-unstable goods. Berisha, Sewak Dubey, and Gharehgozli (2023) and Berisha, Gupta, and Gharehgozli (2024) demonstrated that inflation triggers rapid shifts in income distribution depending on local inequality levels. During the COVID-19 pandemic (2020–2023), Cavallo (2024) found that substituting services with essential goods increased inflation for low-income families, widening inequality. Similarly, Chalise (2026) confirmed that accumulated U.S. inflation from 2013 to 2023 was significantly higher for poorer households due to rising food prices.

Jaravel (2021) consolidated U.S. evidence (1990–2020) into four key insights: (i) the necessity of heterogeneous price indices; (ii) a systematic decline in inflation as household income increases; (iii) technological innovation as a driver of inflation inequality, whereas international trade effects are homogeneous; and (iv) the resulting distortionary impacts on monetary, fiscal, and welfare policies.

Beyond the U.S., a robust literature examines inflation inequality from a global perspective. Binder (2019) used data from up to 146 countries to show that central bank independence weakened the positive correlation between inequality and the inflation tax after 1999. Evaluating the 2022–2024 global cost-of-living crisis, Lokshin, Sajaia, and Torre (2025) found deeper, more prolonged inflationary impacts among low-income groups due to limited budgetary flexibility, a vulnerability also documented by Ndou (2024) for South Africa.

Gürer, and Weichenrieder (2020) identified episodes of pro-rich inflation in Europe, for the period 2010–2019, showing that inequality dynamics depend on the specific price shock. In a broader European study, Neyer, and Stempel (2022) emphasized that monetary policy focusing solely on aggregate averages ignores vital distributive differences, advocating for the explicit incorporation of inflation heterogeneity to mitigate asymmetric welfare impacts.

Euro Area evidence confirms these dynamics. Basso, Dimakou, and Pidkuyko (2022) showed that Spanish inflation (2006–2021) disproportionately affected lower-income households. In Austria, Messner, and Rumler (2024) found significant inflation heterogeneity; while income

disparities are secondary during stable periods, low-income groups face significantly higher inflation during high-inflation regimes. Similarly, Strasser et al. (2023) documented that low-income Euro Area households (2009–2018) experienced higher, though time-varying, inflation. More recently, Kiss, and Strasser (2024) proved that the 2017–2023 inflation shocks more severely impacted lower-income brackets, a regressive pattern supported by Akarsu, and Gharehgozli (2024) and Simionescu (2025).

Turning to the Brazilian experience, there is no empirical application to date of either Unobserved-Components Stochastic Volatility Outlier-adjusted (UCSVO) or Time-Varying Parameter (TVP-Kalman) state-space models to analyze inflation by income group. Nevertheless, the existing literature offers foundational insights into inflation inequality and structural modeling. Silva, and Fonseca Neto (2011) examined the 1994–2010 period and identified a “pro-poor” inflation regime, characterized by systematically higher inflation rates for low-income households, particularly in less developed regions. This greater exposure to inflationary shocks, even during periods of relative macroeconomic stability, is driven by the disproportionate weight of food and essential services in the consumption baskets of these families.

Souza, and M. L. Ferreira (2022) investigated inflation heterogeneity in Brazil from 2010 to 2020, focusing on how monetary policy shocks asymmetrically affect different income strata. Their findings revealed significant inflation differentials driven by the composition of consumption baskets and varying degrees of nominal rigidity across socioeconomic groups. Specifically, the authors documented that negative price shocks are more persistent for lower-income brackets, suggesting that downward price adjustments last longer for the poor. Similarly, M. L. C. Ferreira, and Souza (2023) used quantile regressions to analyze inflation persistence across different income levels in Brazil from 2006 to 2021. They found evidence that the official headline IPCA index fails to capture substantial inflationary heterogeneity across income strata. Moreover, negative shocks exhibit asymmetric persistence, creating more intense, long-lasting impacts for lower-income groups and highlighting the critical need for policymakers to look beyond aggregate metrics to protect vulnerable households.

Regarding the application of unobserved components frameworks, Costa Filho (2023) employed a trend-cycle model with stochastic volatility, following Chan, Clark, and Koop (2018), to estimate Brazilian trend inflation from 2002Q1 to 2022Q4. The author documented a sustained downward trajectory starting in 2017, largely attributed to domestic institutional changes, and demonstrated that this core trend remained resilient against the temporary inflationary surge triggered by the COVID-19 pandemic. Turning to multivariate extensions, Tangza (2019)) applied the MUCSVO model to analyze Brazil’s headline IPCA inflation from January 2000 to June 2019, showing that the underlying structural trend has become progressively less susceptible to idiosyncratic shocks over time.

In the context of time-varying parameter Phillips curves for Brazil, D. Ferreira, and Palma (2015) estimated a generalized Phillips curve (2003–2013), via Kalman filter, and rejected the relationship for Brazil. However, evidence was found of a decreasing trend in short- and

medium-term exchange rate pass-through during the sample period. Similarly, Boaretto, and Gomes da Silva (2018) applied a TVP state-space model to evaluate headline and services inflation (2004–2016). Their findings showed that the coefficient for inflation inertia remained systematically smaller than that of inflation expectations across all specifications. Nonetheless, the backward-looking inertial component proved to be far from negligible.

Therefore, this article provides distinct methodological and empirical contributions to the inflation inequality literature through two fronts. First, using the UCSVO framework, we identify structurally distinct trend and volatility regimes across Brazilian income groups while controlling for extreme events. Second, via a Time-Varying Parameter Phillips Curve, we demonstrate that intrinsic inflation persistence fluctuates dynamically over time for each group, while accounting for the transmission mechanisms of other macroeconomic variables, such as inflation expectations.

4.3 Data

To achieve our goal of investigating inflation inequality across income strata in Brazil from July 2006 to April 2025 using a univariate methodology (UCSVO) and a multivariate technique (TVP-Phillips Curve), we consider the following variables:

- IPCA: National Consumer Price Index (monthly %, seasonally adjusted). Source: Brazilian Institute of Geography and Statistics (IBGE).
- IPCA by Income Group: Consumer Price Index by income group (Very Low, Low, Middle, High) (monthly %, seasonally adjusted). Source: Institute for Applied Economic Research (IPEA).
- IPCA Expectations: One-month-ahead expectations (seasonally adjusted). Source: Central Bank of Brazil (BCB).
- IBC-Br: Central Bank’s Economic Activity Index logarithm, HP-filtered, seasonally adjusted). Source: BCB.
- REER: Real Effective Exchange Rate (logarithm, first difference, seasonally adjusted; 2020=100). Source: Bank for International Settlements (BIS).

The output gap is obtained by applying the Hodrick-Prescott filter to the log-level of the IBC-Br at the monthly frequency, using the standard smoothing parameter $\lambda = 14,400$ for monthly data. The resulting cyclical component is stationary, as confirmed by the unit root tests reported in Table 4.1, and serves as a proxy for domestic demand pressures in the TVP Phillips Curve estimation. Additionally, our decision to employ one-month-ahead inflation expectations, rather than the standard 12-month-ahead horizon, ensures strict methodological and frequency alignment with our monthly inertia component ($\alpha_{1,t}$). This high-frequency approach avoids time-aggregation bias and effectively isolates short-term price dynamics from long-term base

effects. The Supplementary Material (Section S1) provides an extended discussion on inflation expectations data sources, collection procedures, and the specification rationale.

Our primary variable of interest is the disaggregated IPCA by income group, originally developed by Lameiras, Carvalho, and Souza-Júnior (2017), methodologically updated by Lameiras, Carvalho, and Santos (2020), and updated to its current structure in Lameiras (2025). This inflation rate series is published monthly by the IPEA, which defines six distinct socioeconomic tiers based on specific economic thresholds: Very Low, Low, Lower-Middle, Middle, Upper-Middle, and High. However, our econometric analysis focuses on four of these groups, as the Lower-Middle and Upper-Middle tiers exhibit strong convergence with the core Middle group. The Supplementary Material (Section S2) details the socioeconomic context, income standardization (including US dollar equivalence), and consumption weights across cohorts, and the long-run cumulative price trajectories.

Table 4.1 presents the descriptive statistics for all system variables. The monthly inflation average for the very low-income group (0.492%) exceeds the headline IPCA (0.460%), a pattern accompanied by higher volatility (a standard deviation of 0.360% versus 0.294%) and a sharper maximum peak (1.813% versus 1.478%). The low-income cohort displays a similar vulnerable pattern, whereas middle- and high-income groups record historical dynamics closer to or below the national benchmark. To formally confirm whether these long-run trend distributions are structurally and statistically distinct, a non-parametric Friedman validation framework and post-hoc comparisons are provided in Section S3 of the Supplementary Material (Friedman, 1937).

Regarding the remaining macroeconomic variables, the data reveal important patterns about monetary policy anchoring and economic cycles. Inflation expectations average 0.399% per month, remaining structurally below the realized inflation across all income strata (which ranges from 0.452% to 0.492%). This wedge suggests a historical tendency of market expectations to underestimate effective inflationary pressures. The IBC-Br cyclical component, serving as our proxy for the output gap (y_t), exhibits a mean near zero (0.000%) with a standard deviation of 0.021%, accurately capturing the cyclical variations of Brazilian economic activity throughout expansions and contractions. Finally, the first difference of the Real Effective Exchange Rate (REER, Δe_t) presents a neutral mean (-0.001%) but highly volatile fluctuations, ranging from -0.149% to 0.094%, which reflects the substantial exposure of the domestic economy to external currency shocks. Taken together, these metrics provide a robust control framework for estimating the time-varying structural relationships within the Phillips Curve reported in Table 4.1.

Table 4.1 – Descriptive Statistics (% per month)

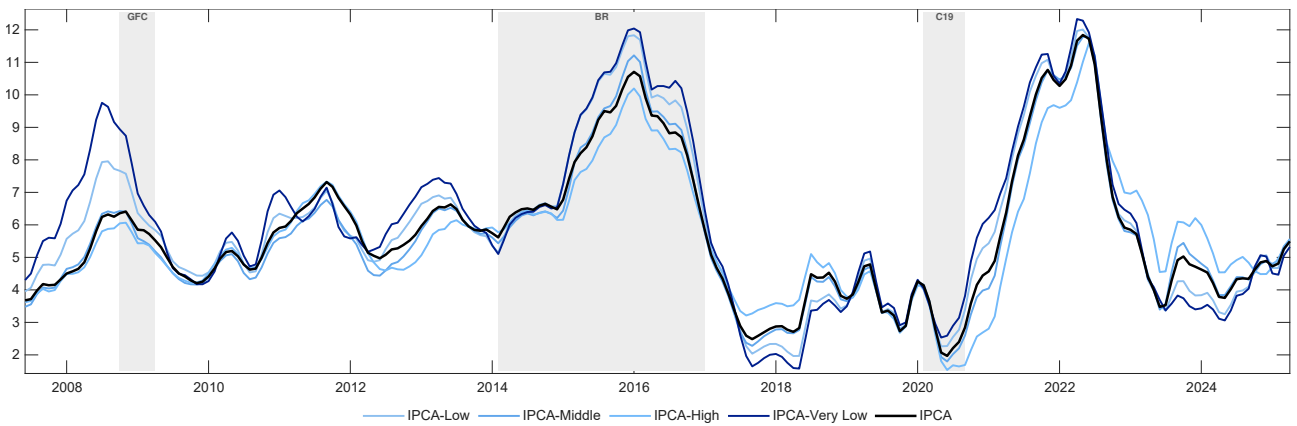
Variable / Stratum	Mean	Median	Max	Min	Std. Dev.
IPCA	0.460	0.421	1.478	-0.566	0.294
IPCA - Very Low	0.492	0.459	1.808	-0.218	0.360
IPCA - Low	0.476	0.450	1.813	-0.307	0.333
IPCA - Middle	0.452	0.410	1.586	-0.756	0.306
IPCA - High	0.452	0.423	1.277	-0.497	0.281
Inflation Expectations	0.399	0.399	1.074	-0.113	0.115
REER (Δe_t)	-0.001	0.001	0.094	-0.149	0.030
IBC-Br (y_t)	0.000	0.003	0.035	-0.138	0.021

Source: Prepared by the author based on IBGE and Lameiras (2025).

Note: IPCA - Lower-Middle and IPCA - Upper-Middle are omitted from the econometric system due to high collinearity and statistical similarity with IPCA - Middle.

Figure 4.1 uncovers the underlying temporal patterns and helps evaluate the historical dynamics of inflation across income groups over time, by tracking the 12-month accumulated inflation across the analyzed strata. The shaded areas denote the recessions detected by the Brazilian Economic Cycle Dating Committee (CODACE/FGV, 2023). The historical trajectories reveal distinct cyclical behaviors and structural vulnerabilities. The high-income group registered prominent peaks of 7.82% in April 2009 and 8.88% in September 2011, episodes heavily linked to demand-side shocks and exchange rate depreciation that disproportionately impacted durable goods and services. By contrast, the very low-income group faced much more severe inflationary spikes, reaching 9.84% in July 2008, 11.86% in December 2015, and peaking at 12.71% in April 2022. This heterogeneity highlights the distributive nature of inflation, which more severely affects lower-income strata, amplifying economic vulnerabilities through different supply and demand channels. The long-run cumulative price index by income stratum, which reveals how these differences compound over time, is presented in Section S2 of the Supplementary Material.

Figure 4.1 – IPCA Inflation Dynamics Across Income Group (12-month cumulative %)



Source: IBGE and Lameiras (2025).

Note: The curves present the heterogeneous inflationary trajectories for the headline IPCA and the specific income groups, ranging from very low income to high income. Shaded vertical bars denote recessions dated by CODACE.

4.4 Econometric Methodologies

4.4.1 Univariate Analysis: The UCSVO Model

The Unobserved-Components Stochastic Volatility Outlier-adjusted (UCSVO) model, developed by Stock, and Watson (2007) and extended by Stock, and Watson (2016), decomposes the inflation rate into permanent and transitory components, where innovations are explicitly adjusted for extreme events (outliers). This framework offers distinct advantages over traditional statistical filters. Unlike rigid methods such as the Hodrick-Prescott (HP) filter, which fail to capture structural breaks, the UCSVO model incorporates time-varying factor loadings and stochastic volatility. This flexible architecture allows the model to accommodate structural shifts in both the persistence and specific volatility of localized inflation series.

Another key strength of the UCSVO framework is its capacity to let the data endogenously determine whether an economic shock permanently shifts the inflation trend or merely represents a high-volatility transitory disturbance, while simultaneously controlling for extreme outliers that would otherwise distort variance estimations. This feature is particularly crucial for emerging economies like Brazil, where low-income consumer baskets are highly vulnerable to frequent food and energy supply shocks.

In this study, the UCSVO model is estimated for the national headline IPCA ($R = 1$) and four of the six income groups considered by IPEA ($R = 2, \dots, 5$), as formalized by the following system of equations:

$$\pi_t^R = \tau_t^R + \varepsilon_t^R \quad (4.1)$$

$$\tau_t^R = \tau_{t-1}^R + \sigma_{\Delta\tau_t^R} \cdot \eta_{\tau,t}^R \quad (4.2)$$

$$\varepsilon_t^R = \sigma_{\varepsilon_t^R} \cdot s_t^R \cdot \eta_{\varepsilon,t}^R \quad (4.3)$$

$$\Delta \ln(\sigma_{\varepsilon_t^R}^2) = \gamma_{\varepsilon}^R \cdot v_{\varepsilon,t}^R \quad (4.4)$$

$$\Delta \ln(\sigma_{\Delta\tau_t^R}^2) = \gamma_{\Delta\tau}^R \cdot v_{\Delta\tau,t}^R \quad (4.5)$$

where π_t^R represents the observed inflation at time t for income group R , τ_t^R is the permanent (or trend) component, and ε_t^R is the transitory component. Equation (4.1) performs the structural decomposition of inflation. Equation (4.2) models the trend as a random walk with stochastic volatility $\sigma_{\Delta\tau_t^R}$, subject to the idiosyncratic shock $\eta_{\tau,t}^R$. From an economic standpoint, τ_t^R captures the long-run inflation anchor and structural price rigidities unique to each income cohort, reflecting permanent structural shifts such as policy changes or long-term agricultural regime shifts.

Equation (4.3) models the transitory component with an adjustment for extreme events through the scale factor s_t^R , which takes the value 1 with probability $(1 - p)$ and uniformly distributed values in the interval $[2, 10]$ with probability p , allowing for the identification of inflationary outliers. Particularly suited for emerging markets like Brazil, this formulation treats short-lived supply shocks (e.g., food seasonality or energy tariff flags) as transitory outliers (ε_t^R).

This ensures that such innovations are not mathematically misabsorbed into the permanent core trend (τ_t^R). Equations (4.4) and (4.5) define the stochastic processes governing the volatility evolution of the transitory component and the trend, respectively. The shocks $\eta_{\varepsilon,t}^R$, $\eta_{\tau,t}^R$, $v_{\varepsilon,t}^R$, and $v_{\Delta\tau,t}^R$ are independent and identically distributed idiosyncratic noises following a standard normal distribution $N(0, 1)$. The joint variance-covariance matrix of these terms is assumed to be an identity matrix I_4 , as specified in Stock, and Watson (2016).

The UCSVO model contains only three primary parameters: γ_ε and $\gamma_{\Delta\tau}$, which are related to the innovations in the stochastic volatility process (Equations 4.4 and 4.5), and p , which represents the prior probability of outliers (Equation 4.3). A Bayesian approach is used in the UCSVO model estimations following the standard empirical literature (Stock, and Watson, 2016). Priors are necessary for the stochastic volatility parameters γ_ε and $\gamma_{\Delta\tau}$, for the outlier probability p , and for the initial values τ_0 , $\ln(\sigma_{\varepsilon,0})$, and $\ln(\sigma_{\Delta\tau,0})$. To ensure a standardized framework, independent uniform priors for γ_ε and $\gamma_{\Delta\tau}$ are defined on the interval $[0, 0.2]$, reflecting the smooth evolution typical of macroeconomic volatility.

The prior for the outlier probability p follows a $Beta(\alpha = 0.025, \beta = 0.975)$ distribution. This conservative baseline implies an ex-ante structural expectation of one extreme outlier every four years ($p = 2.5\%$), preventing the algorithm from misidentifying standard transitory variance as extreme anomalies. However, because the Bayesian framework allows the posterior distribution to be endogenously driven by empirical data, the model remains fully flexible to capture a significantly higher real frequency of outliers. This structural adaptability is essential for emerging economies like Brazil, where actual price disruptions occur far more frequently than in developed markets. Finally, the priors for the initial values τ_0 , $\ln(\sigma_{\varepsilon,0})$, and $\ln(\sigma_{\Delta\tau,0})$ are independent diffuse normal distributions with a mean of zero and a large variance, represented by $N(0, 100)$, ensuring that the initial conditions do not exert a distorting influence on the posterior estimates.

The model estimation is performed using Bayesian methods, specifically Markov Chain Monte Carlo (MCMC) techniques, which allows for robust inference about inflation decomposition and the identification of stochastic volatility over time for each income group. This structure provides valuable empirical evidence on the persistence, dispersion, and occurrence of atypical shocks in inflation between different socioeconomic groups in Brazil. To achieve this, a Gibbs sampling algorithm is implemented to sequentially draw the unobserved states and hyperparameters following the foundational framework of Stock, and Watson (2016). The MCMC protocol is executed with a total of 50,000 iterations, where the first 10,000 draws are discarded as a burn-in period to eliminate the influence of initial values. To mitigate serial autocorrelation among consecutive draws, a thinning interval of 10 is applied to the remaining iterations, yielding 4,000 independent posterior samples for statistical inference.

The choice of the univariate UCSVO framework is dictated by data constraints, as the income-group inflation series released by IPEA do not provide the disaggregated sectoral components and time-varying weights required for a multivariate specification. A broader discussion

on this dimensional limitation and multivariate extensions is presented in the concluding section.

4.4.2 Multivariate Analysis: Time-Varying Parameter Phillips Curve

The univariate analysis outlined above captures the isolated trend, volatility, and outlier dynamics of income-specific inflation. Although this trend analysis enables an investigation into whether a specific inflation rate persistently deviates from its own trend or from the headline index, the framework is designed to isolate unobserved univariate components rather than incorporate external macro-variables. Consequently, the TVP-NKPC serves as a natural complement to capture these broader interactions and account for intrinsic inflation persistence or the inertia originating from past inflation.

To address these structural dynamics, we implement this multivariate framework to evaluate how transmission mechanisms differ across socioeconomic strata. The hybrid specification draws on the New Keynesian Phillips Curve literature (Galí, and Gertler, 1999; Galí, Gertler, and López-Salido, 2001; Blanchard, and Galí, 2007), which demonstrates that the coexistence of forward-looking and backward-looking price-setters generates both inertial and expectational dynamics. An Augmented Hybrid New Keynesian Phillips Curve (NKPC) is specified as follows:

$$\pi_t^R = \alpha_{0,t} + \alpha_{1,t}\pi_{t-1}^R + \alpha_{2,t}E_t\pi_{t+1} + \alpha_{3,t}\Delta e_{t-4} + \alpha_{4,t}y_t + \varepsilon_t, \quad R = 1, \dots, 5, \quad (4.6)$$

where π_t^R represents the inflation rate for the headline IPCA ($R = 1$) and across the four specific income groups ($R = 2, \dots, 5$); $\alpha_{0,t}$ is the time-varying intercept; $\alpha_{1,t}$ captures inflation persistence (inertia); $\alpha_{2,t}$ measures the impact of inflation expectations; $\alpha_{3,t}$ is the coefficient related to the real effective exchange rate; $\alpha_{4,t}$ measures the impact of the output gap (y_t) on inflation; and ε_t is the error term.

From an economic and practical standpoint, allowing these parameters to fluctuate over time is essential for capturing structural transitions in the Brazilian economy, such as changes in monetary policy credibility, trade openness, and consumer behavior. For instance, the relative weight between inertia ($\alpha_{1,t}$) and expectations ($\alpha_{2,t}$) offers a direct metric of central bank anchoring across social classes. Lower-income strata, facing tighter budget constraints and limited financial literacy, are expected to exhibit a higher reliance on backward-looking indexation ($\alpha_{1,t}$). In contrast, wealthier households, with greater access to financial hedges, are likely more responsive to forward-looking policy signals ($\alpha_{2,t}$). Similarly, the output gap coefficient ($\alpha_{4,t}$) evaluates whether demand-driven monetary policy operates with the same intensity and lag across different segments of the population. Complementing these market dynamics, the four-month lag applied to the exchange rate (Δe_{t-4}) is structurally motivated by the empirical literature on emerging markets, reflecting the average time lag required for international supply-chain shocks and cost-push currency variations to effectively propagate into domestic retail consumer prices.

To account for regressor exogeneity assumptions inherent in standard Kalman filter applications, the Phillips curve estimation must address potential endogeneity bias. While using lagged variables (π_{t-1}^R and Δe_{t-4}) eliminates feedback from past shocks, contemporaneous regressors, specifically inflation expectations ($E_t \pi_{t+1}$) and the output gap (y_t), are determined simultaneously with current inflation. To address this structural constraint and avoid arbitrary or overly diffuse priors that could destabilize algorithmic paths, we follow Boaretto, and Gomes da Silva (2018) and adopt a two-stage procedure, utilizing initial GMM estimates to initialize the adaptive state-space model (Hamilton, 1994; Elliott, and Timmermann, 2008).

In the first stage, a time-invariant version of Equation (4.6) is estimated via the Generalized Method of Moments (GMM) for each income group. This initial step neutralizes simultaneous endogeneity, measurement errors in the unobserved output gap, and residual autocorrelation through instrument orthogonality, verified via the Hansen J -test. The GMM framework also ensures valid statistical inference under heteroskedasticity, remaining strictly superior to OLS even where regressor exogeneity cannot be rejected. The resulting GMM unbiased baseline parameters are then used to calibrate the initial state vectors and hyper-parameters. This initialization reduces the sensitivity of the Kalman filter to arbitrary prior choices, ensuring numerical stability and faster convergence toward the true parameter trajectory from the very first periods (Harvey, 1989; Kim, and Nelson, 1999). The complete instrument validity and endogeneity tests, following Hayashi (2000), for all income-group specifications are reported in the Supplementary Material (Section S4).

4.5 Empirical Findings

4.5.1 Preliminary Diagnostics: Unit Root and GMM Testing

Before presenting and discussing the empirical findings from our univariate and multivariate estimations, it is essential to establish the integration order of the time series under analysis. Evaluating the stationarity of these variables at level, or $I(0)$, is a crucial prerequisite to ensure the validity and robustness of the subsequent econometric modeling, preventing issues related to spurious regressions.

To achieve this, comprehensive unit root and stationarity tests were conducted, including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Additionally, the Zivot and Andrews (ZA) unit root test was implemented, which incorporates an endogenous structural break component to ensure that potential parameter shifts do not distort the stationarity inference (Zivot, and Andrews, 1992). The complete results for all analyzed series are presented in Table 4.2. The tests systematically confirm that all analyzed time series are stationary at level, or $I(0)$, validating their suitability for subsequent econometric analysis.

The endogenously identified structural breaks in Table 4.2 align closely with major

macroeconomic shifts in the Brazilian economy. For the IPCA income groups, the structural breaks are concentrated between August and September 2016, a period marked by a severe stagflationary environment characterized by high inflationary pressures and a deep economic recession. The 12-month accumulated IPCA inflation reached 8.97% in August, far exceeding the official 6.5% ceiling. These figures were driven by strong cost-push shocks, including the delayed pass-through effects of currency depreciation, the readjustment of previously regulated administered prices (such as energy and fuel), and climate-induced food supply disturbances. Regarding economic activity, the country's GDP experienced a sharp contraction, leading to an annual decline of 3.3% for 2016. In contrast, the breaks for the real exchange rate (Δe_t) and economic activity (y_t) are strictly clustered around the first half of 2020, capturing the unprecedented global and domestic supply-demand disruptions triggered by the onset of the COVID-19 pandemic.

Given the intrinsic flexibility of the econometric frameworks adopted in this study, explicit dummy variables for structural breaks were purposefully omitted from the core estimations. Both the UCSVO model and the TVP Phillips Curve inherently accommodate continuous shifts in long-run trends, conditional volatility, and parameter evolution over time. By modeling coefficients and variance processes as stochastic latent states, these methodologies endogenously absorb both abrupt macroeconomic shocks and smooth, gradual adjustments. Consequently, this approach circumvents the need for ad hoc exogenous dummy placement.

Table 4.2 – Unit Root Tests

Variables	ADF	PP	ADF-GLS	KPSS	Zivot-Andrews (ZA)	
	Stat.- t	Stat.- t	Stat.- t	Stat.-LM	Stat.- t	Break Date
IPCA	-8.29*	-6.85*	-8.32*	0.09	-9.03*	2016:09
IPCA-Very Low	-8.72*	-4.73*	-8.75*	0.10	-9.46*	2016:08
IPCA-Low	-8.65*	-4.74*	-8.75*	0.08	-7.51*	2016:08
IPCA-Middle	-8.42*	-4.95*	-8.44*	0.08	-9.17*	2016:08
IPCA-High	-8.70*	-7.12*	-8.76*	0.10	-9.47*	2016:09
Inf. Expectations	-3.39*	-3.33*	-8.64*	0.19	-4.85*	2017:03
Real Exch. Rate (Δe_t)	-11.58*	-2.25*	-11.53*	0.17	-11.87*	2020:06
Econ. Activity (y_t)	-6.05*	-5.21*	-5.06*	0.03	-6.26*	2020:03

Note: * indicates rejection of the null hypothesis at 5%. ADF, PP, ADF-GLS: H_0 = unit root; KPSS: H_0 = stationary; ZA: H_0 = unit root with one endogenous structural break (Zivot, and Andrews, 1992). ZA critical value at 5%: -4.80.

Table 4.3 presents the baseline GMM estimations for the hybrid Phillips curves across the aggregate IPCA and the four analyzed income strata. These point estimates serve as the baseline for the initialization process of the time-varying Phillips curves analyzed below. The Hansen J -test systematically confirms the validity of the instrument set across all specifications. Inflation persistence (π_{t-1}) is statistically significant in all specifications, ranging from 0.284 for the middle-income group to 0.397 for the headline IPCA. This variation provides the initial empirical evidence of structural disparities in macroeconomic inertia across different income levels. In contrast, IPCA inflation expectations ($E_t\pi_{t+1}$) are statistically significant

in only 2 out of the 5 estimations, suggesting a potentially weaker anchoring mechanism for lower-income strata over the full sample. Furthermore, while the exchange rate pass-through coefficient (Δe_{t-4}) is highly significant in all income strata, the estimated output gap parameter (y_t) does not achieve statistical significance in any baseline specification.

Table 4.3 – GMM Estimates by Income Group

Dependent Variables	Independent Variables (coefficients and SE)					J Stat (p-value)
	Intercept	π_{t-1}	$E_t\pi_{t+1}$	Δe_{t-4}	y_t	
IPCA	-0.263 (0.207)	0.397* (0.091)	1.354* (0.581)	-1.644* (0.613)	-0.123 (1.353)	6.227 (0.514)
IPCA-Very Low	-0.150 (0.351)	0.382* (0.085)	1.129 (0.947)	-2.044* (0.644)	1.809 (1.168)	2.118 (0.548)
IPCA-Low	-0.371 (0.369)	0.305* (0.098)	1.749 (1.013)	-2.056* (0.699)	1.829 (1.330)	2.114 (0.549)
IPCA-Middle	-0.422 (0.457)	0.284* (0.139)	1.862 (1.281)	-1.892* (0.717)	1.735 (1.315)	2.014 (0.570)
IPCA-High	0.083 (0.072)	0.378* (0.076)	0.494* (0.193)	-0.965* (0.414)	1.127 (0.801)	1.896 (0.863)

Note: * indicates statistical significance at 5%. H_0 (J Test): valid instruments. For the exchange rate: an increase denotes appreciation, and vice-versa. GMM equations estimated without imposing the long-run neutrality restriction.

4.5.2 The UCSVO Estimation Results

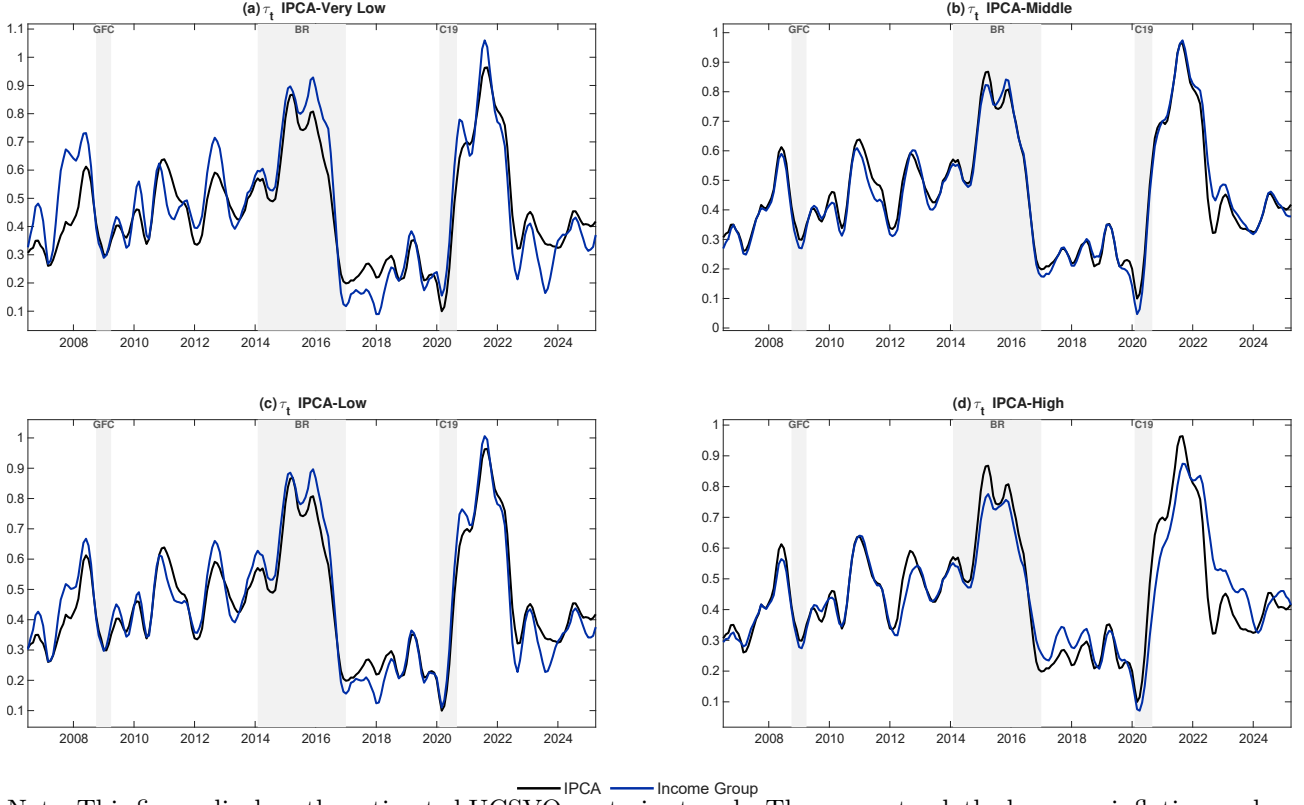
First, we employ the univariate UCSVO model to analyze the evolution of trend inflation, permanent/transitory volatilities, and outliers in different Brazilian households' income groups. Figure 4.2 plots the full-sample posterior means for trend inflation, benchmarking each income-specific rate against the headline IPCA. Panels (4.2a) and (4.2c) indicate that, compared to the headline index, the inflation trend is persistently higher for the very low and low income groups throughout the sample, whereas the rates for the middle and high income groups (Panels 4.2b and 4.2d) follow a trajectory much closer to the national headline trend.

In terms of temporal dynamics, all estimated inflation trends followed a synchronized upward trajectory from 2006 until late 2015. This widespread increase reflects the macroeconomic environment of the period, characterized by the progressive abandonment of the Macroeconomic Tripod (inflation targeting, fiscal surplus targets, and a floating exchange rate) in favor of the interventionist policies associated with the New Economic Matrix. The economic and political turbulence culminated in the Great Brazilian Recession, after which trend inflation steadily declined across all strata until the onset of the COVID-19 pandemic (Fishlow, and Gomes da Silva, 2021).

Beneath these aggregate movements lie profound structural disparities driven by household consumption profiles. Lower-income households are highly vulnerable to price increases in non-discretionary essential goods, such as food and utilities, which exhibit high price rigidity. In contrast, higher-income groups allocate a larger share of their budget to items with higher price elasticity that are less susceptible to supply-side shocks. Wealthier households also pos-

sess greater financial flexibility to substitute consumption patterns, avoiding direct hits to their overall welfare, and hold substantial access to financial instruments that provide real returns, neutralizing the eroding effect of inflation on their purchasing power.

Figure 4.2 – UCSVO Posterior Means: Inflation Trend (τ_t) by Income Group

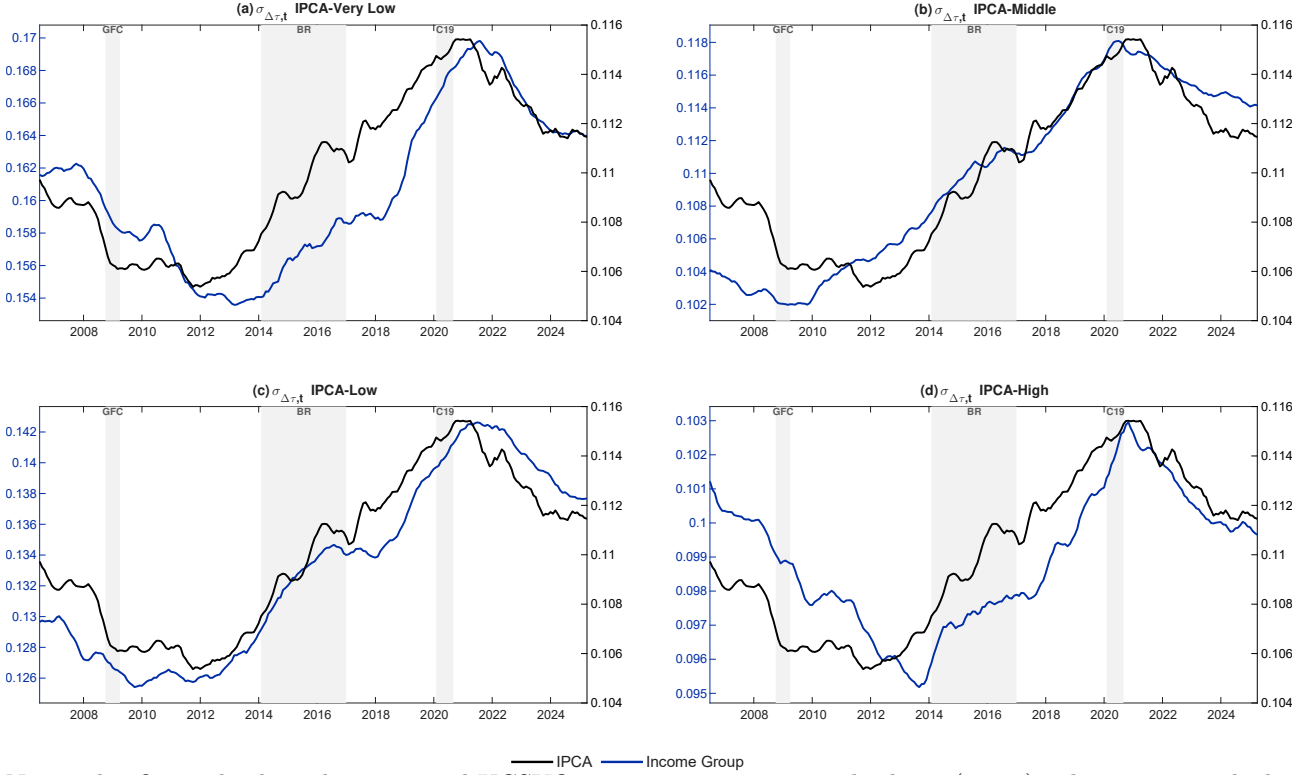


Note: This figure displays the estimated UCSVO posterior trends. The curves track the long-run inflation anchor for the headline IPCA ($R = 1$) and the four income cohorts ($R = 2$ to $R = 5$). Shaded vertical bars denote recessions dated by CODACE.

Figure 4.3 depicts the full-sample posterior means of the permanent volatility component, which plays a critical role in driving the long-run inflation trend. In the Brazilian context, all income groups share a broadly synchronized trajectory, characterized by a steady decline from 2006 until mid-2011, a subsequent upward path leading into the COVID-19 pandemic, and a final downward correction thereafter.

However, a pronounced scale heterogeneity emerges when analyzing the magnitudes of these series, a feature that necessitates the use of a dual-axis presentation to preserve each group's distinct variance dynamics. Although the headline IPCA permanent volatility reaches a maximum peak of 0.116, the very low-income group peaks at 0.170, followed closely by the low-income group at 0.142. In contrast, the middle and high-income groups register substantially lower maximum permanent volatilities of approximately 0.118 and 0.103, respectively. This scale hierarchy explains why the inflation trend of the middle-income group closely mirrors the national benchmark, given their nearly identical variance magnitudes. More importantly, it reveals why the very low and low-income groups exhibit inflation trends that sit persistently and substantially above the headline IPCA, while the high-income cohort experiences a structurally lower baseline.

Figure 4.3 – UCSVO Posterior Means - Permanent Volatility ($\sigma_{\Delta\tau,t}$) by Income Group



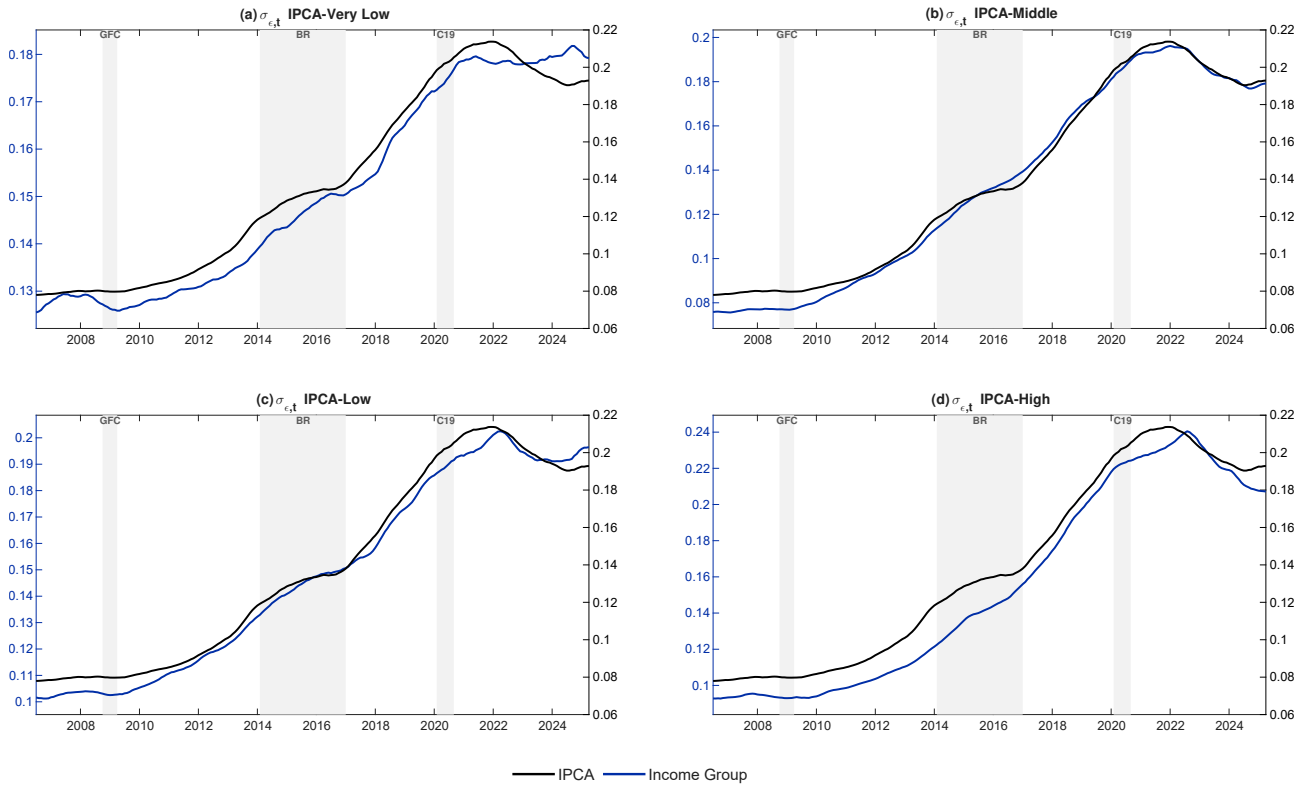
Note: This figure displays the estimated UCSVO posterior permanent volatilities ($\sigma_{\Delta\tau,t}$). The curves track the structural variance of the inflation trend for the headline IPCA and the four income cohorts. Shaded vertical bars denote recessions dated by CODACE.

From a welfare perspective, these percentage-based inflation differences represent the correct metric for assessing economic inequality, as they directly capture the erosion of purchasing power relative to each group's total budget constraint. Lower-income households are structurally exposed to much larger permanent inflationary shocks that fundamentally alter their price trajectory. Because these poorer segments live closer to subsistence levels and have a significantly higher marginal utility of income, a higher percentage inflation rate directly translates into a severe welfare loss, consuming a disproportionate share of their nominal budget. This asymmetric transmission mechanism demonstrates that inflation does not affect the population uniformly, placing a disproportionate and structural burden on the purchasing power of poorer families over the long run.

Figure 4.4 depicts the transitory shock volatility dynamics across different Brazilian household income groups. All groups follow a broadly coherent trajectory, culminating in unprecedented volatility increases during the COVID-19 pandemic, where the headline IPCA peaked at approximately 0.22. Mirroring the permanent volatility pattern, the middle-income group aligns strictly with the headline benchmark throughout the sample. However, a pronounced scale heterogeneity emerges at the opposing ends of the income distribution, necessitating a dual-axis presentation to accurately capture each group's distinct post-crisis behavior. Specifically, the very low and low-income groups registered lower pandemic peaks of around 0.18 and 0.20, respectively, whereas the high-income group experienced the sharpest surge, peaking at almost 0.24.

Regarding the post-pandemic recovery phase, a key distinction lies in the speed of convergence toward pre-crisis volatility levels. For the high-income group, transitory volatility decreased rapidly after the initial pandemic shock. This behavior stems from their larger budgetary allocation to goods and services heavily exposed to global conditions, such as supply chain bottlenecks and international commodity shocks; as these global markets gradually adjusted, transitory volatility for this wealthier demographic collapsed. Conversely, the very low and low-income groups did not exhibit similar convergence. Their transitory volatilities remained elevated, indicating that poorer households continue to endure persistent, highly volatile short-term price disruptions. This reflects the sticky and localized nature of domestic inflationary pressures on essential goods, such as food and basic utilities. Ultimately, this asymmetric post-crisis stabilization highlights that even under transitory shocks, lower-income families face prolonged periods of price instability, fundamentally compounding their overall economic vulnerability (Figure 4.4).

Figure 4.4 – UCSVO Posterior Means - Transitory Volatility ($\sigma_{\varepsilon,t}$) by Income Group

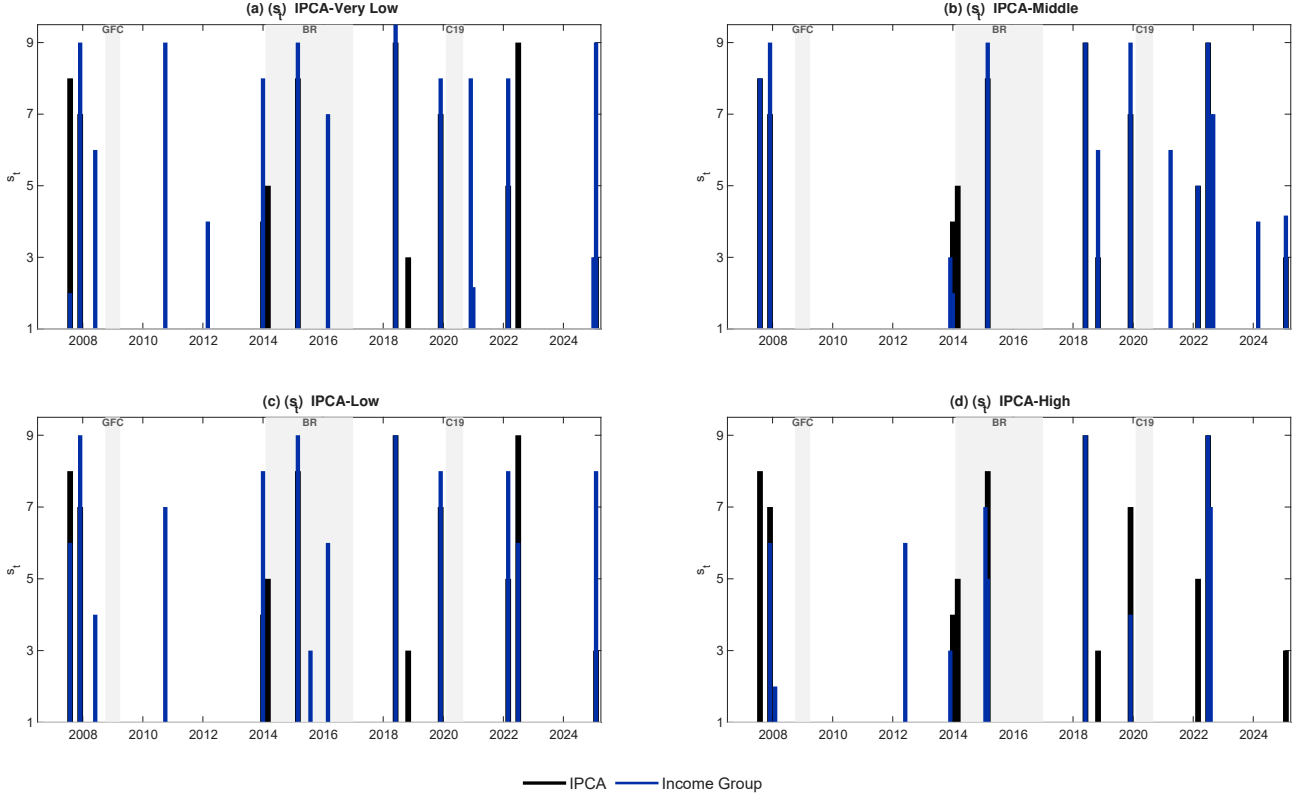


Note: This figure displays the estimated UCSVO posterior transitory volatilities ($\sigma_{\varepsilon,t}$). The curves track the short-run variance of the inflation shocks for the headline IPCA and the four income cohorts. Shaded vertical bars denote recessions dated by CODACE.

Figure 4.5 reveals a considerable asymmetry in both frequency and intensity of the estimated outliers across income groups. The headline IPCA registers only 4 visible outliers throughout the entire sample, each mapped to major macroeconomic disruptions: the 2008 global financial crisis, the onset of the Great Brazilian Recession in 2014, the 2018 truck drivers' strike alongside administered price realignments, and the lingering supply chain disruptions of 2022.

However, a substantial discrepancy emerges when examining the detected outliers for each specific income level. The very low, low, and middle-income groups registered more than 10 outliers over the same period. In sharp contrast, the high-income group experienced far fewer anomalies, totaling approximately 6. This distribution confirms that lower-income households and the middle class are subjected to nearly double or triple the frequency of extreme price shocks compared to wealthier families.

Figure 4.5 – UCSVO Posterior Means - Outliers (s_t) by Income Group



Note: This figure displays the estimated UCSVO posterior inflation outliers. The curves track the identified short-lived extreme supply-side shocks for the headline IPCA and the four income cohorts. Shaded vertical bars denote recessions dated by CODACE.

The underlying structural and macroeconomic mechanisms driving these discrepancies in outlier frequency align with the consumption basket rigidities previously detailed in this study. Because less affluent households allocate a significantly higher portion of their income to non-discretionary items, they are systematically exposed to localized, high-magnitude supply disruptions that often wash out when aggregated into the national index. Ultimately, these findings corroborate the regressive nature of Brazilian inflation, proving that it penalizes vulnerable households not only through permanently higher trends but also through a higher concentration of unpredictable price anomalies.

This empirically documented regressivity and structural vulnerability find strong support in the Brazilian literature on inflation inequality. For instance, Silva, and Fonseca Neto (2011) documented a pro-poor inflation regime for the 1994–2010 period, showing that lower-income households faced systematically higher inflation rates due to the disproportionate weight of food and essential services in their consumption baskets. Souza, and M. L. Ferreira (2022) ex-

tended this evidence to the 2010–2020 decade, finding that inflation differentials across income strata are driven by heterogeneous consumption composition and varying degrees of nominal rigidity, with negative price shocks being more persistent for lower-income brackets. Furthermore, M. L. C. Ferreira, and Souza (2023) utilized quantile regressions to confirm that the official headline IPCA routinely fails to capture inflationary heterogeneity across income strata, reinforcing the need for disaggregated analyses.

The present study advances this literature by providing, for the first time, a structural decomposition of trend, volatility, and outliers by income group using the UCSVO framework. By separating permanent from transitory shocks while explicitly controlling for extreme events, this approach uncovers the precise econometric channels behind the socioeconomic disparities identified by previous authors. To complement this analysis, additional tests were conducted using local projections (Jordà, 2005) to evaluate how a standardized shock propagates dynamically across each income group. As illustrated by the impulse responses presented in the Appendix (Figures 4.7 and 4.8), although these exercises reveal a broadly comparable speed of dynamic transmission across strata, they reinforce that structural inflation inequality is fundamentally driven by variance channels, reflecting the fact that lower-income groups face larger and more frequent volatility shocks in their baseline trend. A comprehensive discussion of these supplementary impulse-response functions, along with their corresponding coefficient tables and sensitivity checks, is provided in Section S4 of the Supplementary Material.

4.5.3 *The TVP Results: Time-Varying Parameter Phillips Curve*

To complement the univariate framework and explicitly account for macroeconomic interactions, the results of the Time-Varying Parameter (TVP) Phillips Curve are presented in Figure 4.6. The primary objective of this model is to isolate the continuous evolution of intrinsic inflation persistence (inertia) across different income strata, while simultaneously evaluating the time-varying impacts of key macroeconomic controls, such as inflation expectations, the output gap, and exchange rate dynamics. Regarding the headline IPCA, Panel 4.6a reveals that its inertia ($\pi_{1,t}$) fluctuates within a relatively bounded range between 0.31 and 0.41, remaining statistically significant throughout the entire sample. To ensure visual clarity and avoid over-cluttering the multi-series plots, the corresponding confidence intervals are omitted from the figures, though their significance is fully confirmed by the underlying estimations.

A disaggregated cross-sectional analysis exposes critical asymmetries in intrinsic persistence that reflect distinct income-specific dynamics. Mirroring the previous unobserved components findings, the middle-income group (Panel 4.6b) closely tracks the trajectory of the headline IPCA, although its magnitude remains persistently lower across the entire sample period, ranging from 0.21 to 0.35. Similarly, the low-income group (Panel 4.6c), with coefficients oscillating between 0.24 and 0.34, exhibits a dynamic behavior that closely mimics the middle-income stratum.

In contrast, the extreme ends of the income distribution display divergent trajectories.

For the very low-income group (Panel 4.6a), the intrinsic persistence begins tightly coupled with the headline IPCA. However, following the severe 2014–2015 macroeconomic crisis, this coefficient decouples and shifts downward, only beginning to re-converge toward the aggregate benchmark in the post-pandemic aftermath. At the other extreme, the high-income group (Panel 4.6d) exhibits the opposite behavior, displaying a persistence trajectory that remains heavily detached from the aggregate IPCA until the 2014–2015 recession. Indeed, this decoupling is so pronounced that a dual-axis presentation is required for this stratum to properly accommodate the substantial differences in magnitude. Between 2016 and the onset of the COVID-19 pandemic, the high-income inertia converged toward the headline index. Yet, triggered by the pandemic shock, it decreased sharply before executing a strong post-crisis recovery to realign once again with the aggregate IPCA dynamics. However, while the lower and middle strata maintain statistical significance throughout the sample, the high-income inertia is mostly non-significant.

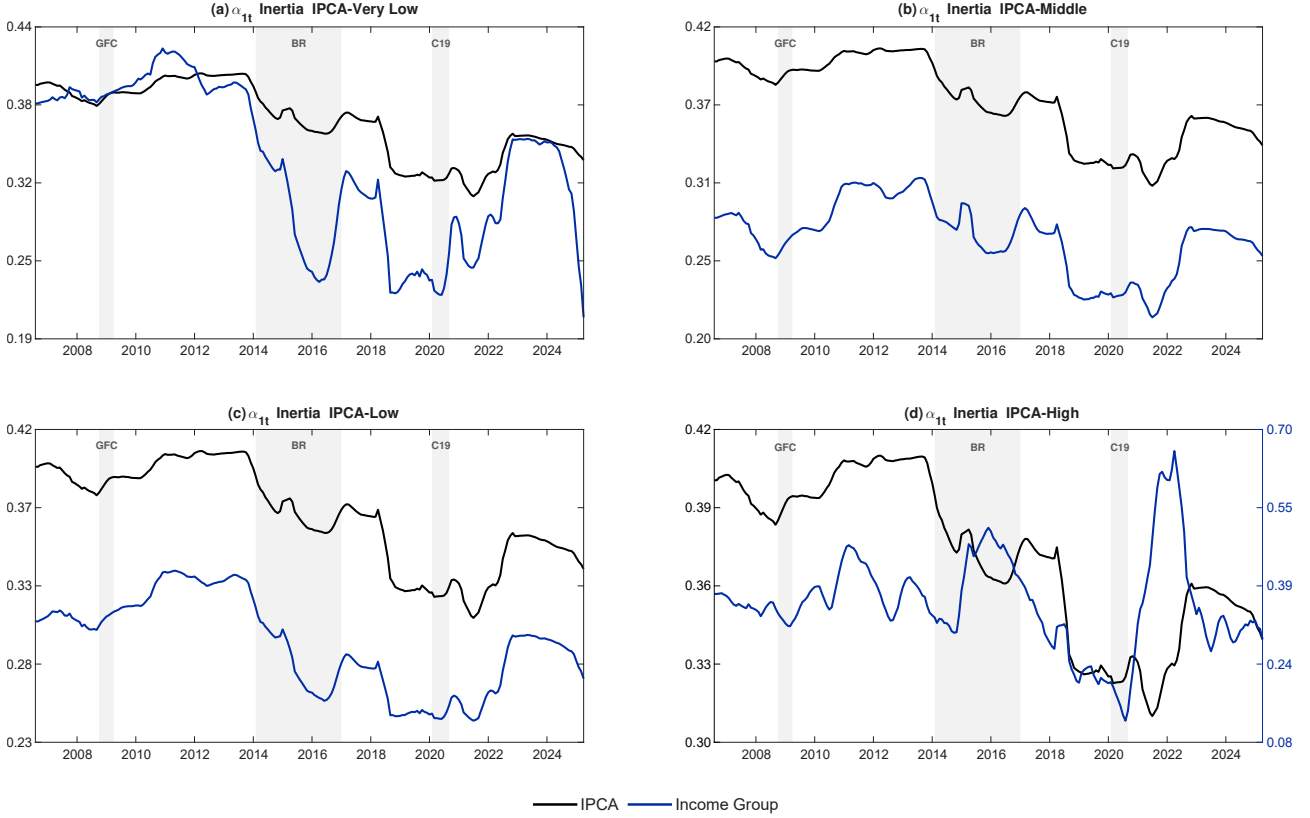
To optimize the manuscript’s visual layout and ensure clear presentation, the figures corresponding to the remaining macroeconomic controls are deferred to the Appendix, while their detailed empirical analysis is provided below. Figure 4.9 indicates that only the high-income group (Panel B), exhibits statistically significant Inflation Expectations coefficients, ranging between 0.30 and 0.50, except for brief periods in 2012 and early 2013. The expectations in the other income groups, although much higher in magnitude than in the high-income case, do not show statistical significance. This uncovers a critical behavioral asymmetry across strata. While lower-income groups are predominantly driven by inflation persistence, the pricing dynamics of the wealthier households are heavily anchored by inflation expectations. This distinction carries profound welfare implications, as the most vulnerable households are constantly forced to catch up with past price increases, lacking the economic mechanisms or financial literacy to effectively anticipate future inflation trends.

Figure 4.10 reports the output gap results, showing that the headline IPCA coefficients reach approximately 2.0, though they only achieve statistical significance from June 2020 onward. The lower- and middle-income strata (Panels a, b, and c) exhibit substantially higher magnitudes and more pronounced peaks, particularly after 2008. In contrast, high-income households (Panel d) show significantly lower coefficients, maintaining significance between January 2009 and September 2019 and from December 2019 onward. This asymmetry stems from distinct consumption structures: lower-income households allocate most of their budget to non-substitutable essential goods, making their inflation highly sensitive to cyclical demand and labor market pressures. In contrast, wealthier households spend a larger share on services and savings, which smooths consumption and insulates their pricing dynamics from sharp output gap fluctuations.

Figure 4.11 reports negative, statistically significant exchange rate pass-through coefficients across all sample periods and income groups. The pass-through magnitude declines monotonically from lower- to higher-income strata. High-income cohorts present smaller, more stable estimates, while the headline IPCA coefficient follows an intermediate path. This pattern

reflects the high exposure of lower-income households to tradable essential goods directly linked to currency fluctuations. Higher-income households allocate larger expenditure shares to non-tradable services, insulating their inflation dynamics from short-run exchange rate movements.

Figure 4.6 – Time-Varying Parameter Phillips Curve: Inertia (α_{1t}) by Income Group



Note: This figure displays the estimated time-varying inflation inertia coefficients ($\alpha_{1,t}$) from the TVP-NKPC model. The curves track the historical evolution of backward-looking price-setting behavior for the headline IPCA and the four income cohorts. To maintain visual clarity across the multi-series panels, the confidence intervals are not graphically displayed but are available upon request. Shaded vertical bars denote recessions dated by CODACE.

4.6 Conclusion

This study analyzed inflation inequality across four income strata in Brazil from July 2006 to April 2025, using the headline IPCA as a benchmark. By combining a Univariate Unobserved Components model with Stochastic Volatility and Outlier Adjustment (UCSVO) and a Time-Varying Parameter (TVP) Phillips Curve, we confirmed our central hypothesis: inflation dynamics in Brazil are structurally unequal, exposing lower-income households to a disproportionately more intense and volatile inflationary process.

The UCSVO permanent volatility component revealed a synchronized historical trajectory since 2006, yet characterized by a pronounced scale hierarchy across the income distribution. The very low- and low-income groups face structurally higher permanent volatility magnitudes compared to the wealthier stratum. This scale asymmetry explains why the long-run inflation trend for the most vulnerable sits persistently and substantially above the headline IPCA benchmark throughout the entire sample. Furthermore, the transitory volatility dynamics

highlighted an asymmetric post-crisis stabilization pattern. The high-income cohort experienced a sharper initial surge during the COVID-19 pandemic driven by global supply shocks, but their volatility collapsed rapidly as international markets adjusted. In contrast, transitory volatilities for lower-income families remained high, demonstrating that poorer households endure prolonged, sticky, and localized short-term price disruptions in essential goods like food and basic utilities.

The TVP Phillips Curve highlighted an asymmetric transmission mechanism throughout the income distribution. While backward-looking inertia drives price dynamics in the lower- and middle-income brackets, wealthy households are primarily influenced by the forward-looking inflation expectations channel. This behavioral asymmetry carries profound welfare implications, as the pricing dynamics of the wealthier stratum are heavily anchored by future expectations, whereas lower-income groups remain highly susceptible to price stickiness and backward-looking inertia, constantly forcing vulnerable households to catch up with past price increases. Furthermore, the macroeconomic sensitivity to the output gap uncovers a stark contrast across classes: lower-income strata exhibit much higher magnitudes and pronounced peaks, reflecting an extreme vulnerability of essential goods to cyclical demand and labor market expansions. Conversely, wealthier households display substantially lower and stable output gap coefficients, as their ability to allocate more income toward services and savings allows them to smooth consumption and insulates their specific pricing dynamics from sharp aggregate demand fluctuations.

From a policy perspective, these findings reveal the inherent limitations of relying exclusively on aggregate inflation measures for economic decision-making. By demonstrating that the output gap influenced lower-income strata as early as 2008, twelve years before its impact became statistically evident in the aggregate IPCA, this study uncovers a substantial “recognition lag” inherent in aggregated indices. A monetary policy strictly guided by the headline IPCA is inherently reactive rather than proactive for the most vulnerable segments. If the central bank ignores these lead-lag disparities and the fact that inflation expectations are exclusively anchored by the high-income group, it risks applying “one-size-fits-all” interest rate interventions that are mistimed, socially regressive, and capable of inadvertently deepening socioeconomic divides.

Despite its contributions, this study is subject to certain limitations that open promising avenues for future research. Although our univariate state-space approach efficiently isolates trend and volatility dynamics for each stratum, it evaluates each income-specific index in isolation. A natural statistical extension is the Multivariate (MUCSVO) framework proposed by Stock, and Watson (2016), which allows for the explicit decomposition of inflation into common macroeconomic shocks and idiosyncratic, sector-specific developments. Currently, this path is constrained by data availability, as the income-stratified datasets provided by IPEA do not deliver the fully disaggregated sectoral series alongside their respective time-varying weights required by the multivariate setup. Alternatively, another promising avenue for future research is to extend the framework into a unified, single-stage Unobserved Components model with an

AR(p) structure and stochastic volatility, directly incorporating time-varying parameter coefficients for the macroeconomic controls within a single-stage optimization procedure. As data infrastructure and computational resources evolve, implementing these alternative state-space structures will provide a richer description of how widespread inflationary trends interact with localized, group-specific shocks in emerging economies.

Consequently, we propose that the Brazilian Central Bank incorporate disaggregated income indicators into its operational framework to monitor the distributional welfare effects of monetary policy. Additionally, because lower-income inflation is structurally driven by permanent shocks to essentials, interest rate adjustments should be complemented by targeted supply-side interventions and social protection programs automatically indexed to income-specific metrics. Acknowledging these structural inequalities is a technical requirement to improve the precision of policy interventions and ensure that price stability translates into broad-based social well-being.

Supplementary Material

The Supplementary Material reports five sets of additional results. Section S1 provides an extended discussion on the data sources of inflation expectations, the collection procedures, and the rationale for the specification. Section S2 details the socioeconomic context, income standardization (including US dollar equivalence), consumption weights between cohorts, and long-term cumulative price trajectories. Section S3 provides the non-parametric Friedman validation framework and post-hoc comparisons. Section S4 reports the complete instrument validity and endogeneity tests for all income-group GMM specifications. Section S5 presents a comprehensive discussion of the additional impulse-response functions and their corresponding lag robustness checks. The main text incorporates the implications of these exercises whenever they are central to the interpretation of the results.

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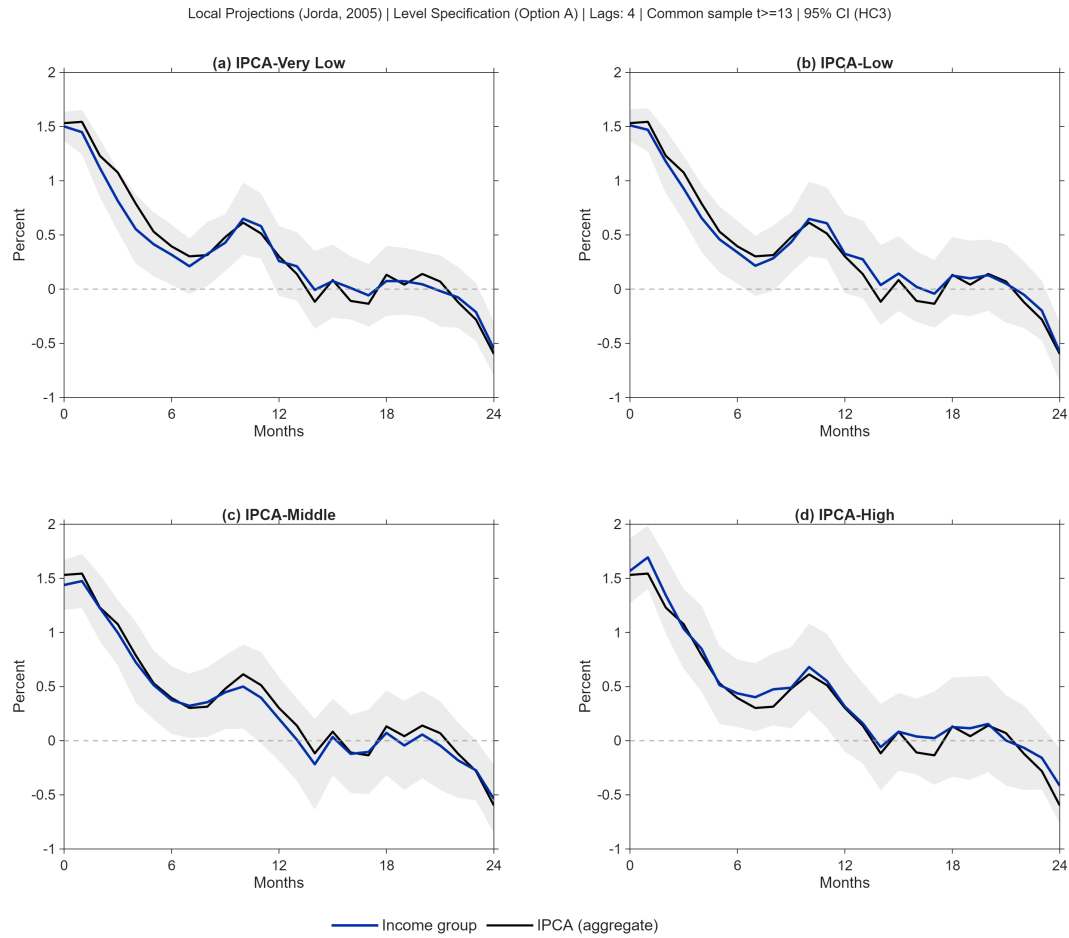
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Appendix: Local Projections

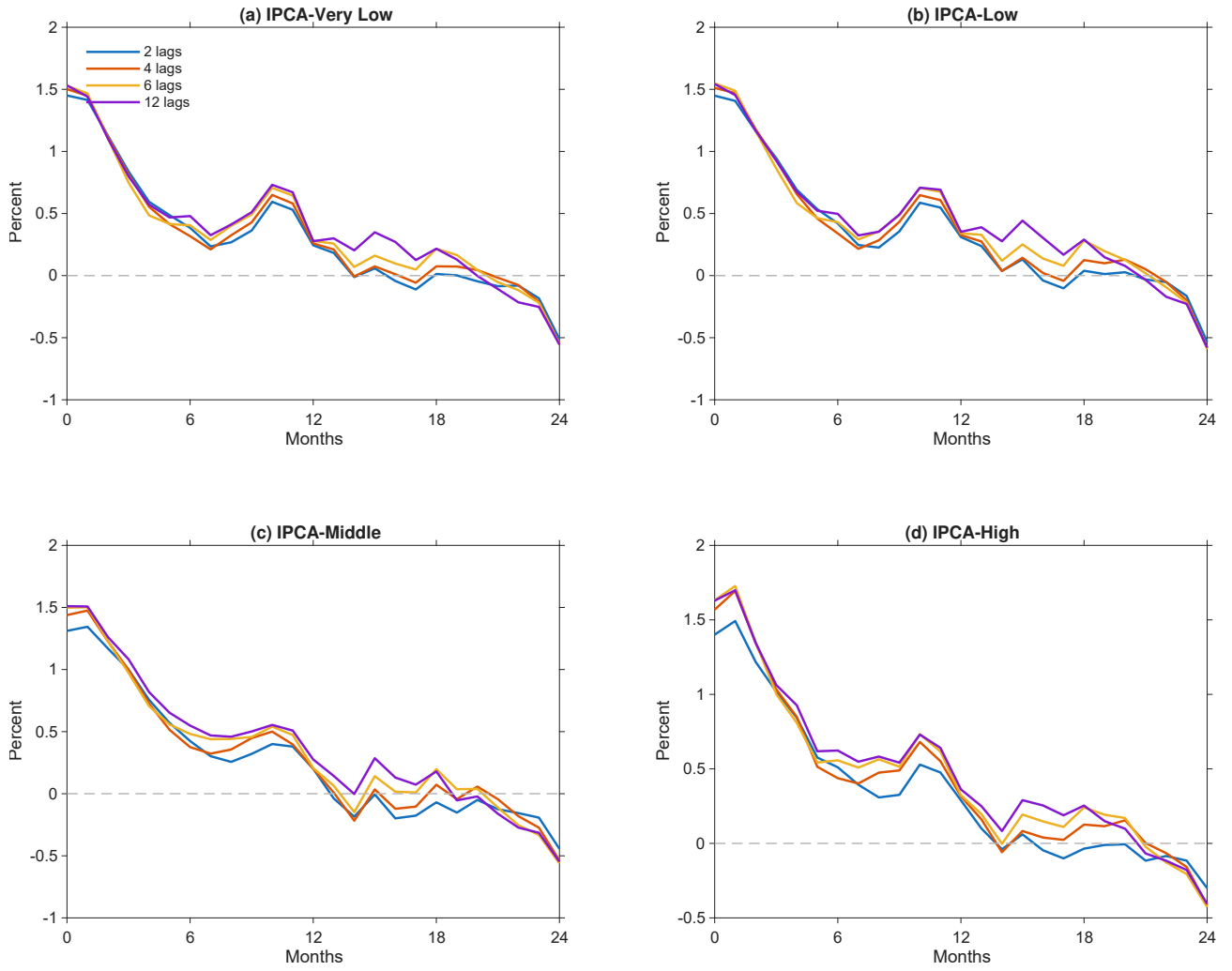
Figure 4.7 – Impulse Responses to a 1 p.p. Trend Shock by Income Group



Note: Local-projection impulse responses (Jordà, 2005) of the inflation level to a one-percentage-point shock to the UCSVO trend $\hat{\tau}_t^R$, by income group, level specification. Solid lines: income-group responses; black line: aggregate IPCA for comparison. Shaded bands: 95% HC3-robust confidence intervals. Common estimation sample ($t \geq 13$). Full coefficients and standard errors are reported in Section 5 of the Supplementary Material.

Figure 4.8 – Local Projections: Robustness to Lag Length by Income Group

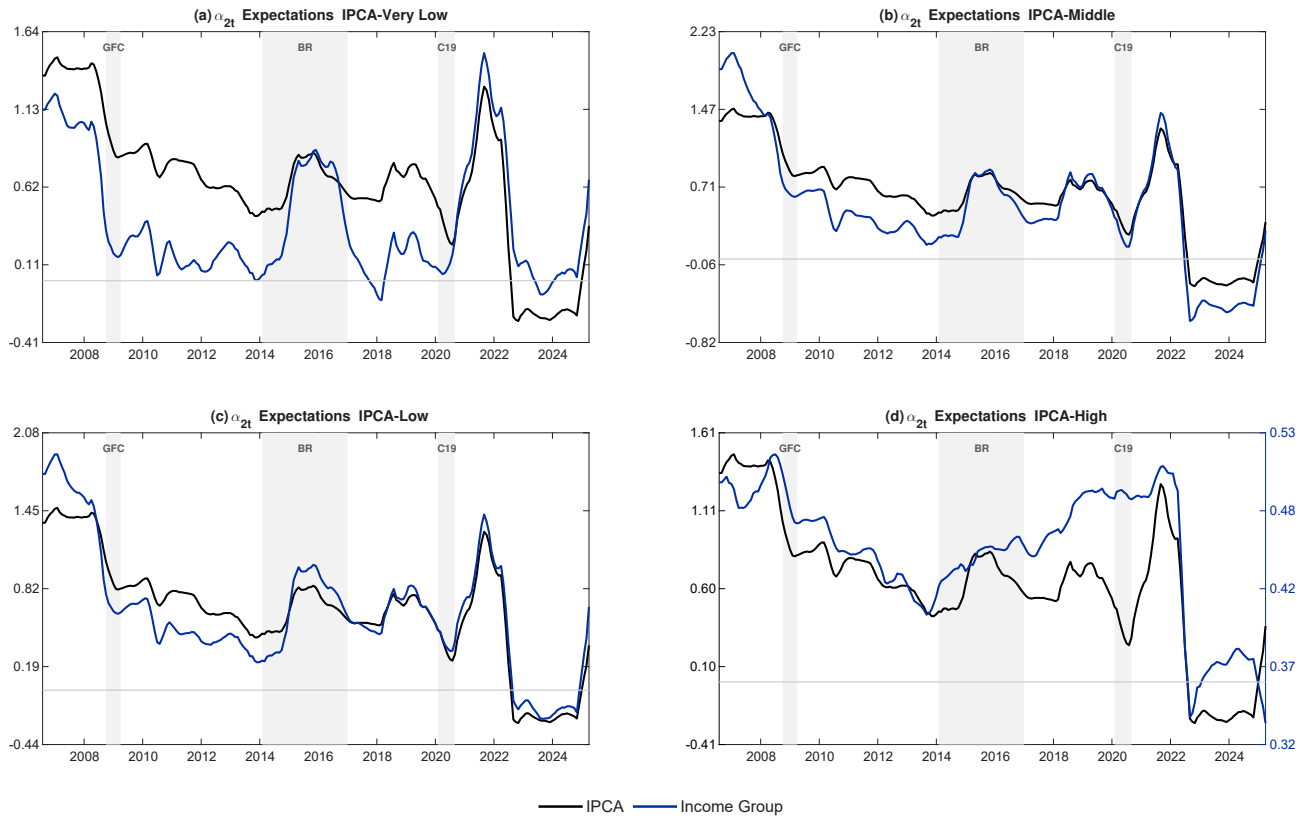
LP Robustness: Sensitivity to Lag Length | Level Specification (Option A) | Common Sample



Note: Local-projection responses estimated with 2, 4, 6 and 12 lags of inflation, holding the estimation sample fixed across variants ($t \geq 13$). The shape and ordering of the responses are stable across lag choices, confirming that the baseline is not driven by the lag specification. A 1 p.p. trend shock; level specification.

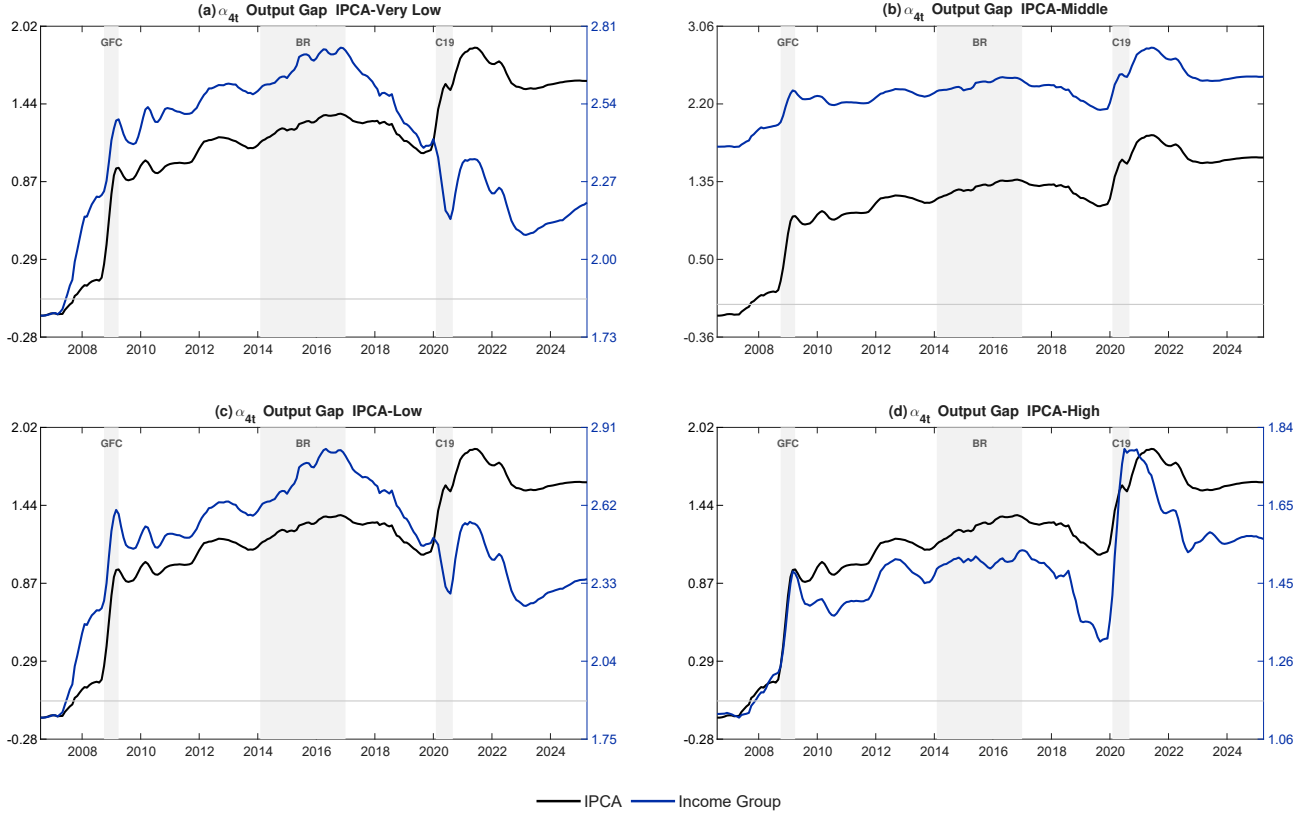
4.7 TVP Phillips Curve: Remaining Controls

Figure 4.9 – TVP Phillips Curve: Inflation Expectations ($\alpha_{2,t}$) by Income Group



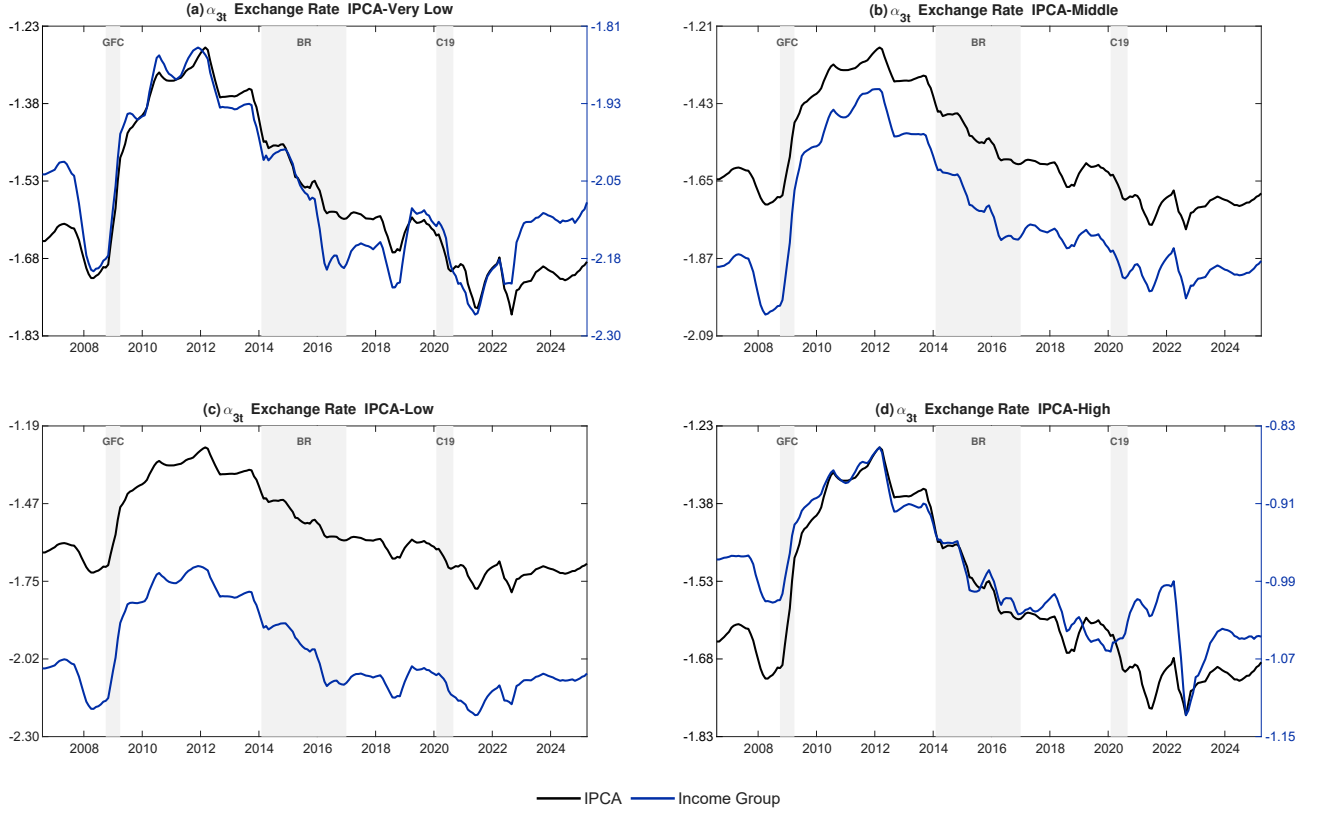
Note: Time-varying inflation expectations coefficients ($\alpha_{2,t}$) from the TVP-NKPC model across the headline IPCA and the four income cohorts. Confidence intervals are omitted for visual clarity but are available upon request. Shaded vertical bars denote recessions dated by CODACE.

Figure 4.10 – TVP Phillips Curve: Output Gap ($\alpha_{3,t}$) by Income Group



Note: Time-varying output gap coefficients ($\alpha_{3,t}$) from the TVP-NKPC model. The IBC-Br is used as a proxy for the output gap. Confidence intervals are omitted for visual clarity but are available upon request. Shaded vertical bars denote recessions dated by CODACE.

Figure 4.11 – TVP Phillips Curve: Exchange Rate Pass-Through ($\alpha_{4,t}$) by Income Group



Note: Time-varying exchange rate pass-through coefficients ($\alpha_{4,t}$) from the TVP-NKPC model. The real effective exchange rate enters with a four-period lag (Δe_{t-4}); an increase denotes appreciation. Confidence intervals are omitted for visual clarity but are available upon request. Shaded vertical bars denote recessions dated by CODACE.

Supplementary Material

The Supplementary Material reports five sets of additional results. Section S1 provides an extended discussion on the data sources of inflation expectations, the collection procedures, and the rationale for the specification. Section S2 details the socioeconomic context, income standardization (including US dollar equivalence), consumption weights between cohorts, and long-term cumulative price trajectories. Section S3 provides the non-parametric Friedman validation framework and post-hoc comparisons. Section S4 reports the complete instrument validity and endogeneity tests for all income-group GMM specifications. Section S5 presents a comprehensive discussion of the additional impulse-response functions and their corresponding lag robustness checks. The main text incorporates the implications of these exercises whenever they are central to the interpretation of the results.

4.8 Inflation Expectations: Data Source, Collection Procedure, and Specification Rationale

As mentioned in the main manuscript, the decision to employ one-month-ahead inflation expectations, rather than the standard 12-month-ahead horizon, ensures strict methodological and frequency alignment with our monthly inertia component ($\alpha_{1,t}$). This high-frequency approach avoids time-aggregation bias and effectively isolates short-term price dynamics from long-term base effects.

A standard specification choice in the empirical New Keynesian Phillips Curve (NKPC) literature is the use of 12-month-ahead inflation expectations or calendar-year projections. However, to rigorously capture short-term inflation inertia, the primary focus of our backward-looking component, the inclusion of accumulated annual figures would be methodologically and macroeconomically counterproductive. From a macroeconomic perspective, 12-month-ahead expectations inherently aggregate prices over a long horizon, embedding a “base effect” from past shocks that smooths out immediate monthly price dynamics. Since tracking monthly inflation inertia requires strict alignment with the high-frequency adjustments of monthly prices, the forward-looking term must operate on the same temporal decision horizon to prevent confounding the estimated time-varying coefficients.

Furthermore, calendar-year expectations create an additional methodological inconsistency in models estimated at a monthly frequency due to their fixed terminal point. This structural feature causes the effective forecast horizon to continuously shrink throughout the year: the expectation recorded in January spans approximately 12 months, whereas the same indicator recorded in November spans only one month toward the exact same endpoint. This structural shrinking is inherent to the 12-month-ahead horizon of the Banco Central do Brasil (BCB) Focus Survey or the Consumer Expectations Series published by FGV/IBRE, introducing substantial heterogeneity in the informational content of the variable across calendar cycles and violating the assumption of a stationary expectation formation mechanism.

Econometrically, mixing monthly inflation series with a 12-month horizon variable would introduce an implicit moving-average structure into the error term, leading to time-aggregation bias and an additional source of endogeneity beyond that already addressed by our Generalized Method of Moments (GMM) estimator. Therefore, we directly employ one-month-ahead inflation expectations sourced from the Central Bank of Brazil. This high-frequency proxy ensures a consistent matching framework across all variables in our system, allowing the time-varying coefficients for both inflation persistence ($\alpha_{1,t}$) and expectations ($\alpha_{2,t}$) to cleanly isolate contemporary structural shifts without contamination from long-term base effects or shrinking-horizon distortions.

Therefore, the underlying raw data for this high-frequency proxy were obtained from the Market Expectations System ("Sistema Expectativas de Mercado") of the Banco Central do Brasil (BCB), available at <https://bcb.gov.br/#/consultas>. To extract the series, we accessed the "Séries de Estatísticas" module and set the following parameters: indicator group "Índices

de Preços"; indicator "IPCA"; periodicity "Mensal"; calculation base "Expectativas informadas nos últimos 30 dias"; and summary statistic "Mediana". Due to a platform constraint limiting downloads to ten-year windows, two separate extractions were required to cover the full sample period, which were subsequently merged.

The platform returns a matrix of daily observations where each row corresponds to a business day and each column represents a future target month. To construct a consistent monthly time series, the observation retained for each target month t was the value recorded in column t on the first available business day of month $t - 1$, thereby capturing the market consensus immediately before within-month forecast revisions. Finally, the raw series was seasonally adjusted in EViews using an additive decomposition method. This seasonally adjusted series constitutes the final expectation variable utilized in all econometric estimations reported in the main text.

4.9 Socioeconomic Context, Income Standardization, and Consumption Profiles

This section details the socioeconomic context, income standardization procedures, and consumption weight architectures across the studied household cohorts. For socioeconomic contextualization, household income brackets were standardized based on the Brazilian Monthly Minimum Wage (MW) effective in January 2025 (BRL 1,518; approximately USD 251). While the Institute for Applied Economic Research (IPEA) defines six distinct socioeconomic tiers based on these institutional thresholds, our core econometric analysis targets four main groups to map structural macroeconomic behaviors. Table 4.4 documents the comprehensive breakdown of the original IPEA income ranges, their corresponding US dollar equivalences, and their respective sample proportions, which provide the statistical foundation for the targeted groups evaluated in the main text.

Table 4.4 – Sample Distribution by IPEA Income Groups (January 2025 Base)

Socioeconomic Class	Minimum Wage Range (MW)	Income Equiv. (USD)	Sample Share (%)
IPCA-Very Low	Less than 1.45	< 364	29.3
IPCA-Low	1.45 to 2.18	364–546	17.5
IPCA-Lower-Middle	2.18 to 3.63	546–910	21.3
IPCA-Middle	3.63 to 7.25	910–1,821	20.1
IPCA-Upper-Middle	7.25 to 14.51	1,821–3,641	8.3
IPCA-High	Greater than 14.51	> 3,641	3.6

The disaggregated inflation indicators follow a Laspeyres index methodology, with base-line consumption weights derived from the 2008/2009 Consumer Expenditure Survey (POF) conducted by the IBGE. These weights are dynamically updated over time by IPEA based on the relative price variations of individual IPCA subitems, thereby tracing the shifting consumption dynamics and structural expenditure patterns of Brazilian households across the distribution.

The empirical update published by Lameiras (2025) underscores this persistent inflation inequality for April 2025. Although focused on a specific cross-section, this snapshot serves as a highly representative baseline illustrating how inflation differentials characteristically manifest across distinct income strata in Brazil. During this specific month, monthly inflation for the very low-income group reached 0.60%, capturing modest reliefs from administered electricity prices. In contrast, the high-income demographic recorded a price increase of just 0.14%, heavily driven by sharp deflationary movements in airfares and automotive fuels. Over the corresponding twelve-month accumulated period, the very low-income segment experienced the lowest inflation rate among all groups (5.43%), while the middle-income cohort faced the highest aggregate burden (5.56%).

These pricing discrepancies do not stem from asymmetric localized price variations, given that all strata face the exact same nominal price signals measured across the country by the Brazilian Institute of Geography and Statistics (IBGE). Instead, the deeply distributive nature of inflation is entirely driven by heterogeneous household budgetary structures. Consequently, identical macroeconomic price shocks, such as climate-driven fluctuations in food supply, exert highly unequal economic pressures across income tiers. This structural divergence underpins the indicator’s construction, which has become increasingly vital for analyzing monetary and economic policy during distributive shocks or high-inflation regimes.

To make these structural differences more evident, Table 3 of the main text presents the relative expenditure weights by consumption group for the six socioeconomic cohorts analyzed, incorporating the headline IPCA as a comparative reference. Reflecting the 2017/2018 Consumer Expenditure Survey (POF) architecture and subsequent methodological updates from Lameiras, Carvalho, and Santos (2020), the dataset reveals stark asymmetries in household budget allocations. For instance, a clear substitution pattern emerges between survival-driven and mobility-driven expenditures. While the Food and Beverages component accounts for a substantial 25.8% of the total budget within the very low-income group, this share drops by more than half to 12.3% for the high-income segment. Conversely, Transportation displays the inverse trajectory, nearly doubling from 13.1% in the poorest stratum to peak at 24.6% in the upper-middle class, establishing itself as the heaviest budgetary burden for middle- and upper-income tiers.

Table 4.5 – Consumption Basket Weights by CPI Income Group (%)

	Very Low	Low	Lower-Middle	Middle	Upper-Middle	High	Headline IPCA
Food and Beverages	25.8	23.4	21.8	18.3	15.5	12.3	19.8
Housing	20.3	18.8	16.7	13.8	13.7	10.9	15.6
Household Items	5.1	4.2	4.0	3.3	3.1	2.9	3.6
Clothing	5.1	4.4	5.0	4.6	4.0	3.9	4.5
Transportation	13.1	17.0	20.3	23.8	24.6	24.0	19.9
Health and Personal Care	10.5	11.8	13.0	13.9	14.1	12.9	13.6
Personal Expenses	7.0	8.0	8.0	9.7	12.2	18.8	10.7
Education	4.1	4.6	4.6	6.7	7.0	10.2	6.4
Communication	5.9	6.0	6.7	5.9	5.7	4.1	5.7

Source: Prepared by the author based on Lameiras (2025).

Additionally, the expenditure data expose severe gaps in discretionary and human capital spending. Personal Expenses and Education act as prominent socioeconomic dividers; the high-income group allocates 18.8% and 10.2% of their total budget to these categories, respectively, which represents roughly three times the proportions spent by the very low-income cohort (7.0% and 4.1%). Housing also exhibits a highly regressive trend, consuming over a fifth (20.3%) of very low-income budgets compared to just 10.9% for the wealthiest stratum. These cross-sectional heterogeneities confirm that the headline IPCA weight baseline (e.g., 19.8% for food and 19.9% for transport) heavily masks the asymmetric vulnerabilities of polarized income strata to specific macroeconomic shocks, thereby validating the deployment of a disaggregated analytical approach.

Regarding the choice of metric, the monthly percentage variation is the standard unit employed in the inflation inequality literature and constitutes the natural measure for capturing the high-frequency erosion of purchasing power across groups that face identical nominal prices but hold heterogeneous consumption baskets. Because all strata are subject to the same price changes measured by the IBGE, the distributive asymmetry arises exclusively from differential basket weights, which the percentage-change metric directly captures through the Laspeyres aggregation structure. Level-based or expenditure-weighted welfare measures, while informative in principle, would require household-level expenditure data at a monthly frequency, which are unavailable for Brazil at the level of disaggregation required here. The income-specific IPCA series provided by IPEA are constructed precisely to translate identical price signals into heterogeneous real burdens through differential basket weights, making the monthly percentage variation the methodologically appropriate and internally consistent metric for this analysis.

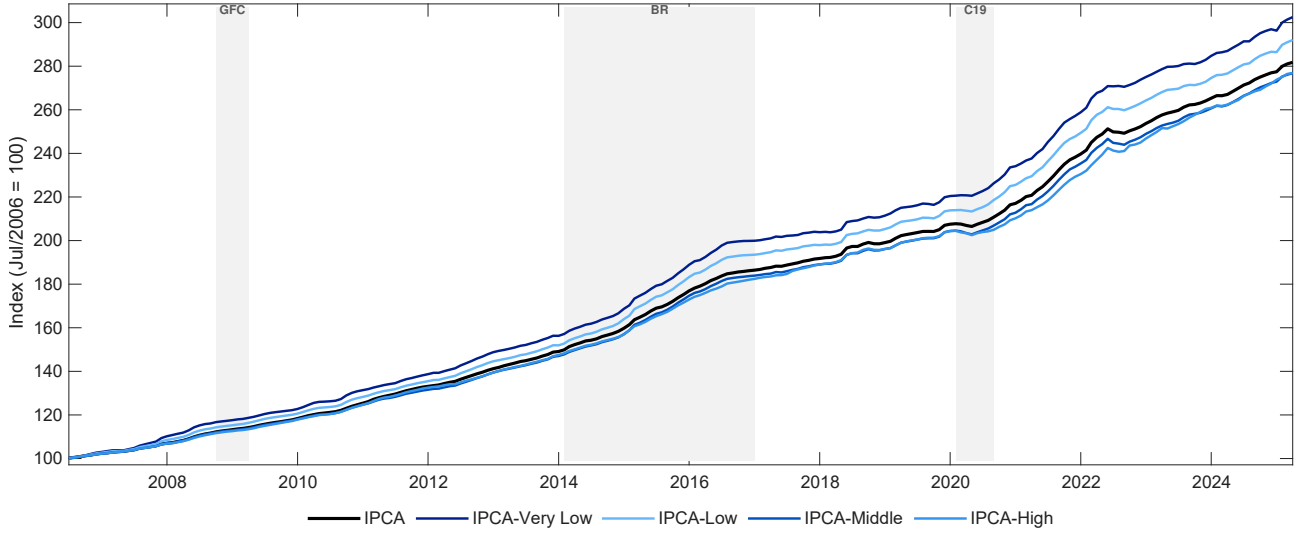
4.9.1 Cumulative Price Index by Income Group

Although the 12-month accumulated rates in Figure 1 of the main text successfully illustrate historical spikes, they only capture cyclical variations rather than the long-term compounding effects of inflation. To reveal how these persistent differences accumulate and widen the purchasing power gap over time, it is necessary to examine a fixed-base price index. This is precisely the purpose of Figure 1 of the main text, which depicts the accumulated evolution of the consumer price index (IPCA) in Brazil from July 2006 to April 2025, with values normalized to 100 in 2006M07.

It is evident that households in the very low and low income groups have experienced consistently higher accumulated inflation compared to middle and high income groups, as well as the Headline IPCA index. This disparity reflects the greater exposure of lower income groups to essential and volatile goods, such as food and energy, that carry a significant weight in the overall consumption basket. Inflation inequality intensifies during periods of macroeconomic shocks, notably the 2015–2016 recession and the post-pandemic inflation surge, which disproportionately affect price dynamics and purchasing power across socioeconomic strata. By April 2025, the accumulated index for the very low-income group reached 301.15, compared to 281.44 for the aggregate IPCA, highlighting persistent distributive imbalances in price formation and

their macroeconomic implications on inequality and economic stability.

Figure 4.12 – Cumulative Inflation Impact by Income Group



Source: IBGE and Lameiras (2025). Note: Shaded areas denote recessions dated by CODACE/FGV.

4.10 Statistical Validation: Friedman Test

While the state-space estimations provide a dynamic decomposition of trend and volatility, evaluating the baseline structural differences across income strata requires formal statistical corroboration. To provide this robust empirical backing, we apply the non-parametric Friedman test for repeated measures directly to the UCSVO-estimated trend series ($\hat{\tau}_t$) across the four income groups ($T = 226$ months, from July 2006 to April 2025). The test evaluates the following structural hypotheses:

H_0 : The trend inflation distributions share identical locations (equal ranks across strata).

H_1 : At least one income stratum exhibits a systematically shifted location.

The choice of the Friedman test is methodologically critical for timeline datasets in emerging markets. Conventional parametric ANOVA or Kruskal-Wallis tests treat the 226 monthly observations as completely independent samples, thereby conflating the massive longitudinal variance (within-group macroeconomic volatility and transitory shocks) with the cross-sectional variance (between-group inequality). This structural contamination biases standard parametric inference toward a false non-rejection of H_0 . By blocking the temporal effect and ranking the income strata within each individual calendar month, the Friedman test successfully filters out aggregate macroeconomic innovations common to all cohorts and isolates the persistent cross-sectional inequality signal.

The empirical results strongly reject the null hypothesis of equal stochastic location among the four income groups ($\chi^2(3) = 17.02$, $p = 0.0007$). The Kendall concordance coefficient ($W = 0.0251$) measures the effect size of the rank agreement; its modest magnitude is expected

with a long $T = 226$ block horizon and reflects that, while the underlying rank differences are genuine and statistically robust, all groups share the same overarching macroeconomic cycles.

To isolate the specific boundaries of this inflation inequality, Panel C reports the post-hoc pairwise Wilcoxon signed-rank tests computed with a conservative Bonferroni correction ($n_{\text{pairs}} = 6$). The matrix establishes our first formal proof of structural inflation heterogeneity, demonstrating that the permanent trends of the most vulnerable cohorts, Very Low-income ($p_{\text{adj}} = 0.0142$) and Low-income ($p_{\text{adj}} = 0.0041$) groups, carry systematically and statistically higher trend inflation ranks than the Middle-income group. Conversely, the High-income group does not statistically differentiate from the other strata in terms of rank location. This specific pattern reinforces that aggregate metrics mask an unequal regressive burden concentrated at the bottom of the income distribution.

Table 4.6 – Friedman Test for Equality of Trend Inflation Across Income Groups

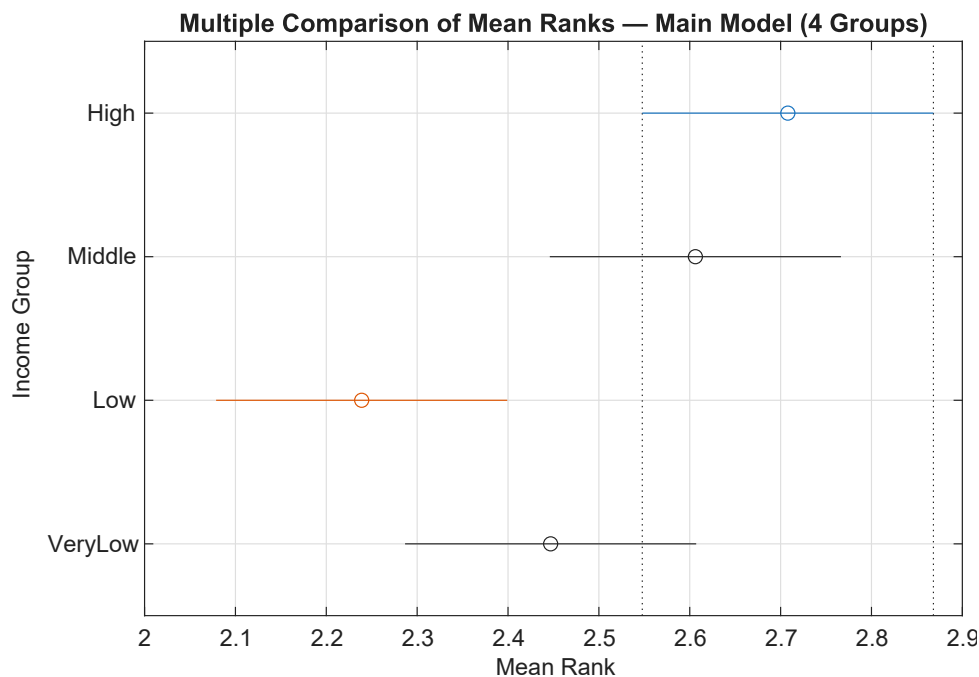
Panel A: Friedman Repeated-Measures Test					
Specification	Groups	χ^2	df	p -value	Kendall's W
Main (Phillips Curve consistent)	4	17.0177	3	0.0007***	0.0251
Panel B: Descriptive Statistics (4 groups)					
Income Group	N	Mean	Median	Mean Rank	
VeryLow	226	0.4698	0.4352	2.7080	
Low	226	0.4603	0.4332	2.6062	
Middle	226	0.4484	0.4137	2.2389	
High	226	0.4527	0.4355	2.4469	
Panel C: Post-hoc Wilcoxon + Bonferroni (4 groups)					
Pair	Mean Diff	Z	p (raw)	p (adj.)	
VeryLow vs Low	+0.0095	2.1407	0.0323	0.1938	
VeryLow vs Middle	+0.0214	3.0400	0.0024	0.0142*	
VeryLow vs High	+0.0171	1.8246	0.0681	0.4083	
Low vs Middle	+0.0118	3.3977	0.0007	0.0041**	
Low vs High	+0.0075	1.5055	0.1322	0.7931	
Middle vs High	−0.0043	−1.6620	0.0965	0.5790	

Notes: Friedman repeated-measures test (Friedman, 1937) blocks by time period ($T = 226$, 2006M07–2025M04). The aggregate IPCA is excluded as it is a weighted average of the income groups. Mean ranks computed row-wise following the Friedman procedure. Panel C: pairwise Wilcoxon signed-rank tests utilizing the normal approximation with Bonferroni correction ($n_{\text{pairs}} = 6$). Z -statistic reported. Kendall's $W = \chi^2/[T(k-1)]$ measures the effect size of the rank concordance. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Figure 4.13 displays the multiple comparison of mean ranks graphically for the four-group specification. Intervals that do not overlap with the reference vertical line indicate statistically significant pairwise differences at the 5% level after Bonferroni correction. The x -axis displays the estimated mean rank for each income group; thus, non-overlapping intervals with the vertical reference line provide a direct visual identification of statistically significant pairwise differences. The underlying test results ($\chi^2(3) = 17.02$, $p < 0.001$) confirm that the strata

do not share a common stochastic location. For the precise pairwise p -values and exact rank values, see Table 4.6.

Figure 4.13 – Post-Hoc Multiple Comparisons of Trend Inflation Mean Ranks



Note: Intervals indicate pairwise comparisons with Bonferroni correction based on the Friedman test ($T = 226$, 2006M07–2025M04) at the 5% significance level.

4.11 GMM Instruments and Endogeneity Tests

As mentioned in the main manuscript, the first step in our empirical strategy is to estimate the Phillips Curve equation for each income group using the Generalized Method of Moments (GMM). This initial step neutralizes simultaneous endogeneity and residual autocorrelation through instrument orthogonality, which is formally validated via the Hansen J -test. The resulting unbiased baseline GMM parameters are subsequently used to calibrate the initial state vectors and hyperparameters. This initialization strategy reduces the sensitivity of the Kalman filter to arbitrary prior choices, ensuring numerical stability and accelerating convergence toward the true parameter trajectory from the very first periods. Therefore, this supplementary section documents the instrument sets used and presents the empirical results of the endogeneity tests.

Table 4.7 documents the complete instrument set used in each GMM specification. Each group-specific instrument list was selected to satisfy both the relevance and exogeneity conditions. Relevance is provided by exploiting inflation persistence via lags of the dependent variables, which are denoted by rmb_sa , rb_sa , rme_sa , ra_sa , and $ipca_sa$ for the very low, low, middle, high, and headline IPCA income groups, respectively. To capture cost-push and demand-pull variations that are predetermined at the estimation date, we include lags of the log

first difference of the nominal exchange rate (BRL/USD), denoted as Δlc , and the output gap (hp) estimated by the Hodrick-Prescott filter applied to the IBC-Br index. For the high-income group, we additionally include lags of one-month-ahead inflation expectations from the BCB Focus survey ($expec$).

The number of instruments varies across groups, reflecting degrees-of-freedom constraints and the group-specific autocorrelation structure confirmed by pre-estimation diagnostic tests. This careful selection avoids instrument proliferation, and the statistical validity of the instrument sets is formally confirmed by the Hansen J -test reported in the main text.

Table 4.7 – GMM Instrument Sets by Income Group

Income Group	Instruments
IPCA-Very Low	$rm_sa_{t-1}, rm_sa_{t-2}, rm_sa_{t-3}, \Delta lc_{t-4}, \Delta lc_{t-6}, hp_{t-1}, hp_{t-2}$
IPCA-Low	$rb_sa_{t-1}, rb_sa_{t-2}, rb_sa_{t-3}, \Delta lc_{t-4}, \Delta lc_{t-6}, hp_{t-1}, hp_{t-2}$
IPCA-Middle	$rme_sa_{t-1}, rme_sa_{t-2}, rme_sa_{t-3}, \Delta lc_{t-4}, \Delta lc_{t-6}, hp_{t-1}, hp_{t-2}$
IPCA-High	$ra_sa_{t-1}, ra_sa_{t-2}, ra_sa_{t-3}, expec_{t-1}, expec_{t-2}, \Delta lc_{t-4}, \Delta lc_{t-5}, hp_{t-1}, hp_{t-2}$
IPCA (Headline)	$ipca_sa_{t-1}, ipca_sa_{t-2}, ipca_sa_{t-5}, ipca_sa_{t-7}, ipca_sa_{t-9}, \Delta lc_{t-4}, \Delta lc_{t-6}, \Delta lc_{t-8}, hp_{t-2}, hp_{t-3}, hp_{t-5}$

Notes: All inflation rates and expectations are seasonally adjusted (sa). Subscript $t - j$ indicates a j -period lag. Variable definitions and data sources are detailed in the text.

Regarding the endogeneity tests, we focused exclusively on the two variables with the highest probability of being endogenous due to their contemporaneous nature. The endogeneity of Inflation Expectations ($E_t\pi_{t+1}$) and the Output Gap (y_t) was assessed using the difference-in- J -statistics test (Hayashi, 2000). This procedure compares the J -statistic of the unrestricted GMM model, where $E_t\pi_{t+1}$ and y_t are treated as endogenous, with that of a restricted model where both variables are added to the instrument list and treated as exogenous. Under the null hypothesis that both regressors are exogenous, the difference in J -statistics is asymptotically distributed as $\chi^2(2)$.

Table 4.8 reports the empirical results. The endogeneity test rejects the null hypothesis at the 5% significance level only for the aggregate IPCA ($p = 0.0272$), confirming the presence of simultaneous determination between inflation expectations, the output gap, and headline inflation. For the four individual income strata, the null hypothesis cannot be rejected, indicating that expectations and the output gap can be treated as pre-determined or exogenous within these specific subgroups. This suggests that simultaneity bias is primarily an aggregate phenomenon, likely driven by the compounding effects of macroeconomic feedback loops that disappear at disaggregated levels.

Even in specifications where the null hypothesis of exogeneity is not rejected, the GMM framework remains strictly superior to Ordinary Least Squares (OLS) estimation. First, the output gap is an unobservable variable estimated via statistical filtering, a process known to induce classical measurement errors that bias OLS estimates toward zero. Second, disaggregated inflation dynamics are highly susceptible to unobserved supply shocks and changing policy en-

vironments, which can become trapped in the error term and generate omitted-variable bias. Finally, by incorporating a Heteroskedasticity and Autocorrelation Consistent (HAC) weighting matrix, the GMM estimator ensures valid statistical inference in the presence of serial correlation and time-varying volatility, which are ubiquitous features of monthly inflation data. Therefore, the instrument sets described in Table 4.7 provide consistent, robust, and immune parameter estimates across all income groups by construction, with global instrument validity verified by the Hansen J -test.

Table 4.8 – Regressor Endogeneity Test ($E_t\pi_{t+1}$ and y_t)

Income Group	Diff. in J -stats	df	p -value
IPCA	7.2118	2	0.0272**
IPCA-Very Low	1.9785	2	0.3719
IPCA-Low	3.0301	2	0.2198
IPCA-Middle	3.7187	2	0.1558
IPCA-High	2.8826	2	0.2366

Notes: ** indicates rejection of the null hypothesis at the 5% significance level.

4.12 Local Projections: Dynamic Responses to a Trend Shock

This section traces, for each income stratum, the dynamic response of inflation to a shock in the trend component recovered from the first-stage UCSVO model, and documents the robustness check that supports it. The exercise is a reduced-form complement to the structural analysis. It takes the UCSVO trend $\hat{\tau}_t^R$ as given and characterises how that trend propagates through observed inflation. It is therefore not a test of the UCSVO or the TVP Phillips Curve, but an independent dynamic perspective to be read alongside them.

Specification

Let $\hat{\tau}_t^R$ denote the posterior-mean trend estimated by the UCSVO model for income group R (Section 4.1 of the main text). Following Jordà (2005), for each horizon $h = 0, 1, \dots, 24$, we estimate the following local projection via OLS separately for the aggregate IPCA and for the four income strata:

$$\pi_{t+h}^R = \alpha_h^R + \beta_h^R \hat{\tau}_t^R + \sum_{k=1}^4 \gamma_{k,h}^R \pi_{t-k}^R + u_{t+h}^R. \quad (4.7)$$

In this setup, α_h^R represents a horizon-specific constant, $\gamma_{k,h}^R$ denotes the autoregressive coefficients capturing internal inflation momentum, and u_{t+h}^R is the forecast error term. Because the dependent variable π_{t+h}^R spans shifting horizons while the information set remains fixed at time t , the error term u_{t+h}^R inherently follows a moving average process of order h . This serial correlation structure is fully corrected during inference through the implementation of a Heteroskedasticity and Autocorrelation Consistent (HAC) variance-covariance estimator, specifically using HC3 heteroskedasticity-robust standard errors to construct our 95% confidence intervals.

The coefficient β_h^R traces the response of the inflation level at horizon h to a one-percentage-point shock to the estimated monthly trend. Estimating the inflation level directly, rather than a cumulative difference, makes β_h^R comparable across groups by construction. The specification conditions on four lags of the inflation level π_{t-k}^R , which control for the pre-shock trajectory without blocking the transmission channels of interest.

The contemporaneous macroeconomic variables from the Phillips-curve stage (inflation expectations, the output gap, and the exchange rate) are intentionally excluded from this exercise. These variables operate as post-treatment transmission channels of the initial trend innovation, meaning that conditioning on them would block the structural propagation mechanisms this analysis is designed to isolate. Finally, to ensure that the baseline estimates, the lag-robustness checks, and the standardized-shock tables remain strictly comparable, all specifications share a common estimation sample that begins immediately after the maximum lag length considered ($t \geq 13$).

Results

Table 4.9 reports the coefficients along with their corresponding HC3-robust standard errors at selected horizons and Figure 4.14 plots the estimated impulse responses. The central finding is that a highly synchronized dynamic pattern emerges across all income strata. Impulse responses exhibit a remarkably uniform trajectory and timing across specifications, with minor discrepancies in point magnitudes remaining statistically indistinguishable due to the substantial overlap of the 95% confidence intervals.

At impact ($h = 0$), the response is positive and highly significant for all groups, ranging from 1.44 (Middle) to 1.57 (High), with t -statistics spanning between 10 and 22. This contemporaneous positive effect reflects the direct pass-through of trend innovations to observed monthly inflation. When the permanent component of the price index rises by one percentage point, the current inflation level rises by a near-proportional amount across all strata, confirming that trend shocks are immediately absorbed into prices regardless of income group.

The inflationary impulse declines monotonically over subsequent horizons, showing high synchronization across all specifications. The impact remains strongly significant at $h = 3$ (ranging from 0.815 to 1.076) before narrowing at $h = 6$ and largely dissipating by $h = 12$, where only the Low-income stratum retains marginal significance. By $h = 18$, the response is statistically indistinguishable from zero for every group. At the extended horizon ($h = 24$), all strata display a modest but statistically significant negative coefficient, ranging from -0.416 (High) to -0.598 (IPCA aggregate).

This late sign reversal reflects a standard mean-reversion process, where monthly inflation temporarily dips below the pre-shock baseline as prices converge toward their new long-run equilibrium path. While the point estimates are numerically larger in absolute value for lower-income cohorts (Very Low: -0.551 ; Low: -0.581) than for the High-income group (-0.416), these differences are not statistically distinguishable due to overlapping confidence intervals.

Table 4.9 – Impulse-Response to a 1 p.p. Trend Shock – Level Specification

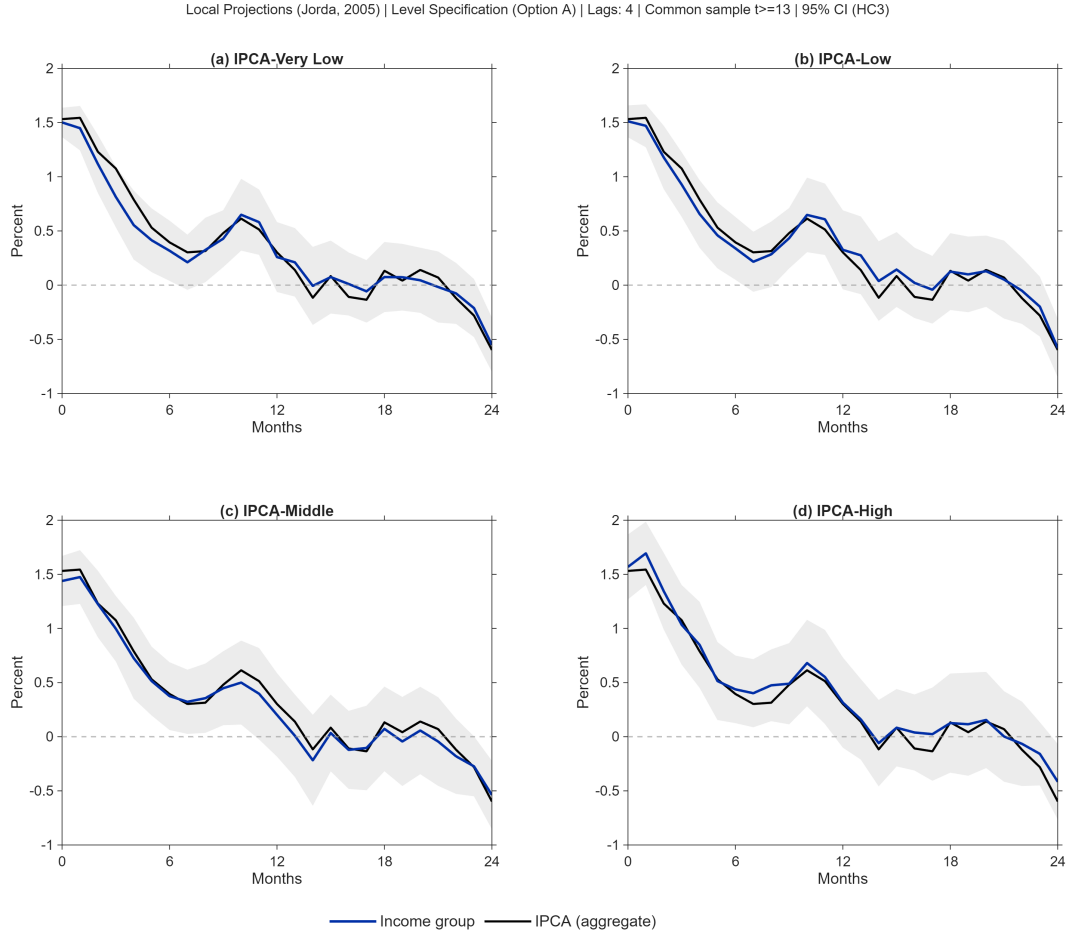
Income Group	$h = 0$	$h = 3$	$h = 6$	$h = 12$	$h = 18$	$h = 24$
IPCA (aggregate)	1.532*** (0.114)	1.076*** (0.155)	0.395** (0.165)	0.302 (0.187)	0.133 (0.201)	−0.598*** (0.151)
IPCA-Very Low	1.501*** (0.069)	0.815*** (0.143)	0.318** (0.142)	0.259 (0.164)	0.075 (0.165)	−0.551*** (0.127)
IPCA-Low	1.511*** (0.075)	0.928*** (0.152)	0.340** (0.148)	0.326* (0.186)	0.125 (0.181)	−0.581*** (0.138)
IPCA-Middle	1.439*** (0.118)	0.998*** (0.154)	0.375** (0.160)	0.202 (0.197)	0.072 (0.199)	−0.538*** (0.161)
IPCA-High	1.569*** (0.153)	1.034*** (0.187)	0.438*** (0.159)	0.315 (0.212)	0.126 (0.234)	−0.416** (0.178)

Notes: Estimated coefficient $\hat{\beta}_h^R$ from $\pi_{t+h}^R = \alpha_h^R + \beta_h^R \hat{\tau}_t^R + \sum_{k=1}^4 \gamma_k \pi_{t-k}^R + u_{t+h}^R$, where $\hat{\tau}_t^R$ is the UCSVO-estimated trend for income group R (Jordà, 2005). HC3-robust standard errors in parentheses. *, **, ***: significance at 10%, 5%, 1%. Common estimation sample ($t \geq 13$), 2006M07–2025M04.

The lesson learned is that the near-uniform timing and shape of the transmission confirm that structural inflation inequality is not driven by heterogeneous propagation speeds. Instead, it operates through the variance channels documented by the UCSVO model, characterized by larger permanent volatility, higher transitory volatility, and a greater incidence of outliers for lower-income cohorts, as well as the asymmetric expectations anchoring found in the TVP Phillips Curve.

Having established the core dynamic properties of the baseline model, we next verify the stability of these trajectories under alternative autoregressive structures to ensure that our central insights are methodologically robust. The baseline Equation (4.7) utilizes four lags of inflation. To verify that this specific lag selection does not drive our empirical conclusions, particularly regarding the estimated persistence and the long-run sign reversal, the level projections are re-estimated using alternative lag lengths of 2, 4, 6, and 12. For this sensitivity check, we hold the estimation sample strictly fixed across all specifications ($t \geq 13$, starting immediately after the maximum lag length considered) to ensure that the comparisons are not contaminated by varying historical sample windows.

Figure 4.14 – Impulse Responses to a 1 p.p. Trend Shock by Income Strata



Note: Local-projection impulse responses (Jordà, 2005) of the inflation level to a one-percentage-point shock to the UCSVO trend $\hat{\tau}_t^R$, by income group, level specification. Solid lines: income-group responses; black line: aggregate IPCA for comparison. Shaded bands: 95% HC3-robust confidence intervals. Common estimation sample ($t \geq 13$).

Equation (4.7) utilizes four lags of inflation as its baseline specification. To verify that this lag selection does not drive our empirical conclusions, we re-estimate the level projections using alternative lag structures of 2, 4, 6, and 12 lags. For this sensitivity check, we hold the estimation sample strictly fixed across all specifications ($t \geq 13$, starting immediately after the maximum lag length considered) to ensure that the comparisons are not contaminated by varying historical sample windows.

Table 4.10 and Figure 4.15 demonstrate that both the overall shape of the dynamic responses and the ordering across income groups are highly stable. At the intermediate horizon ($h = 12$), the point estimates remain positive and closely aligned with the baseline results (e.g., hovering around 0.30 for the aggregate IPCA). At the extended horizon ($h = 24$), the coefficients vary within a very narrow band (approximately ± 0.1 p.p.), and the relative position of the strata is perfectly preserved across all lag choices.

Table 4.10 – Local Projections: Robustness to Lag Length

Income Group	$h = 12$				$h = 24$			
	2	4	6	12	2	4	6	12
IPCA	0.293	0.302	0.293	0.316	−0.513	−0.598	−0.626	−0.607
Very Low	0.244	0.259	0.280	0.278	−0.511	−0.551	−0.554	−0.556
Low	0.311	0.326	0.340	0.352	−0.534	−0.581	−0.591	−0.581
Middle	0.201	0.202	0.206	0.276	−0.445	−0.538	−0.561	−0.548
High	0.289	0.315	0.323	0.362	−0.301	−0.416	−0.428	−0.407

Notes: Estimated coefficient $\hat{\beta}_h^R$ on a 1 p.p. trend shock, level specification (Equation 4.7). Common estimation sample ($t \geq 13$). HC3-robust.

To fully contextualize these dynamic transmissions within the core theme of structural inflation inequality, Table 4.11 documents the long-run responses scaled by a group-specific one-standard-deviation trend shock ($\hat{\sigma}_\tau$) derived from the first-stage UCSVO model. While a standardized 1 p.p. impulse indicates that propagation speeds are nearly uniform across cohorts, scaling the shock by the actual historical volatility faced by each stratum uncovers a stark distributional gap.

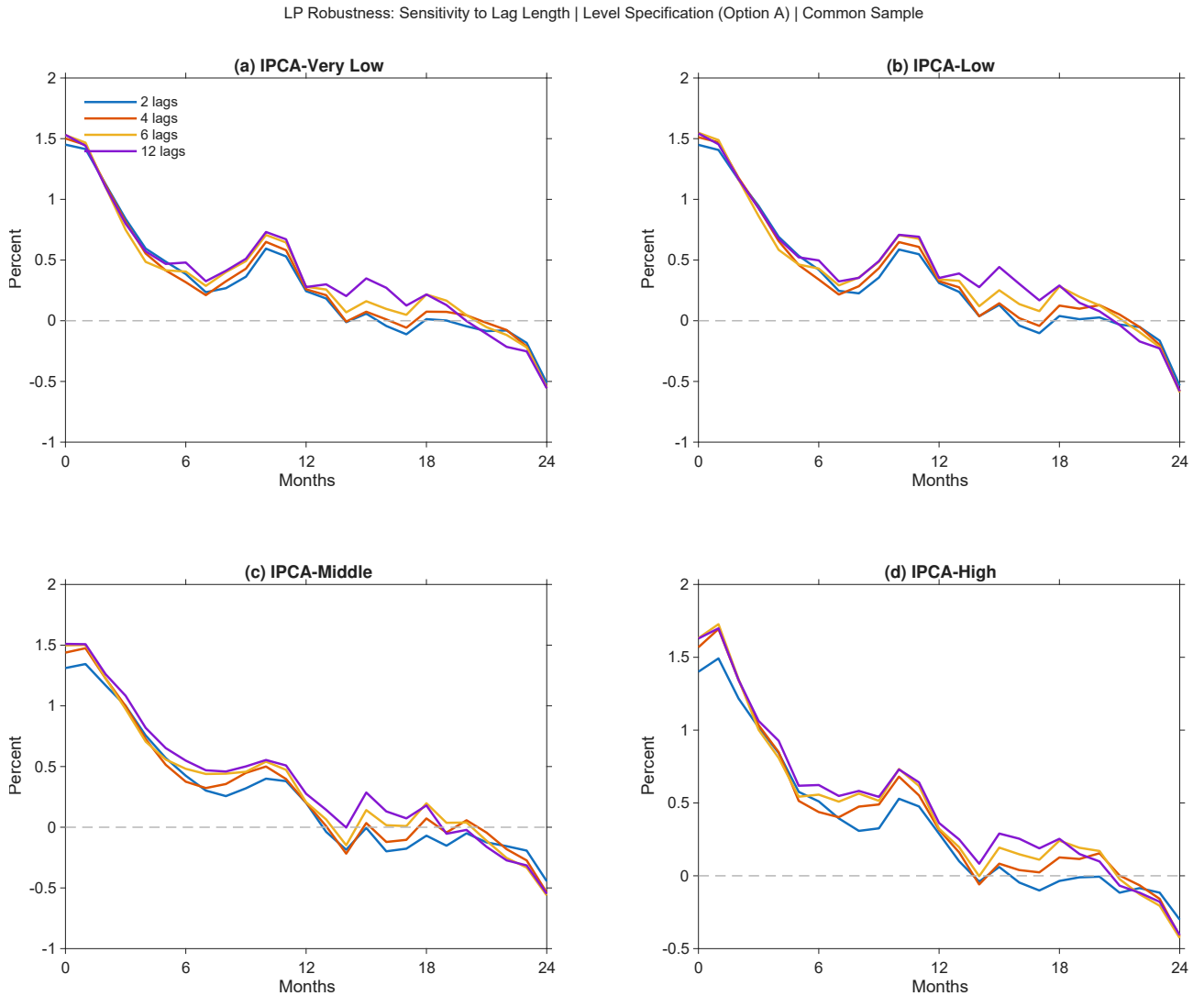
The dynamic long-run adjustment at $h = 24$ is substantially more severe for the Very Low (−0.135 p.p.) and Low (−0.131 p.p.) income groups than for the High-income cohort (−0.074 p.p.). This evidence confirms that structural inflation inequality does not operate through asymmetric transmission speeds, but rather through the variance channels mapped by the UCSVO framework: lower-income households are systematically exposed to larger and more frequent permanent shocks, compounded by higher transitory volatility and an elevated incidence of extreme outliers in their consumption baskets.

Table 4.11 – Local Projections: Response to a One-Standard-Deviation Trend Shock ($h = 24$)

Income Group	$\hat{\sigma}_\tau$	$\hat{\beta}_{24}$ (1 s.d.)	SE	95% CI
IPCA	0.200	−0.120	0.030	[−0.179, −0.060]
Very Low	0.244	−0.135	0.031	[−0.195, −0.074]
Low	0.226	−0.131	0.031	[−0.192, −0.070]
Middle	0.204	−0.110	0.033	[−0.174, −0.045]

Notes: Response at $h = 24$ to a shock equal to one historical standard deviation ($\hat{\sigma}_\tau$) of the trend $\hat{\tau}_t^R$. Common estimation sample ($t \geq 13$). HC3-robust standard errors.

Figure 4.15 – Local Projections: Robustness to Lag Length by Income Strata



Notes: Level-projection responses estimated with alternative lag structures (2, 4, 6, and 12 lags of inflation) under a common estimation sample ($t \geq 13$). The overall dynamic shape and cross-group ordering are fully preserved across lag choices. A 1 p.p. trend shock.

4.12.1 Local Projections: Robustness to Macroeconomic Controls

A natural concern is whether the dynamic response documented above reflects the trend shock itself or merely co-movement with contemporaneous macroeconomic conditions. To ad-

dress this, we augment the baseline local projection in Equation (4.7) with the three macroeconomic variables of the Phillips-curve stage, namely inflation expectations ($E_t\pi_{t+1}$), the output gap (y_t , HP-filtered) and the real exchange rate variation (Δe_t):

$$\pi_{t+h}^R = \alpha_h^R + \beta_h^R \hat{\tau}_t^R + \sum_{k=1}^4 \gamma_{k,h}^R \pi_{t-k}^R + \delta_{1,h} E_t\pi_{t+1} + \delta_{2,h} y_t + \delta_{3,h} \Delta e_t + u_{t+h}^R. \quad (4.8)$$

We stress that this is a sensitivity check rather than our preferred specification. As discussed in the baseline, these three variables are not exogenous covariates but post-treatment channels through which a trend shock propagates to inflation; including them therefore risks partialling out part of the very effect β_h^R is meant to capture. We report the exercise precisely to show that this concern does not overturn the results. Estimation uses HC3-robust standard errors on the common sample ($t \geq 13$).

Table 4.12 contrasts the baseline coefficient with the controlled estimate at $h = 12$ and $h = 24$, and Figure 4.16 plots the two response paths for each stratum together with the 95% confidence band of the baseline. The dynamic response is qualitatively robust to the inclusion of macroeconomic controls. The sign, timing and overall profile of the impulse response are preserved across all income groups: a positive impact that decays through the first year and turns negative by the end of the second. At $h = 12$ the controlled coefficients are modestly larger than the baseline (by roughly 0.02 to 0.10 percentage points), and at $h = 24$ they are modestly less negative (by roughly 0.05 to 0.12 percentage points). These differences are small relative to the HC3-robust standard errors: as Figure 4.16 makes clear, the controlled response lies within the baseline confidence band at every horizon and for every income group, so the two specifications are not statistically distinguishable. The income ordering of the long-run reversal is also unchanged: it remains largest in absolute value for the lower-income strata and smallest for the high-income group, although, as in the baseline, the overlapping confidence intervals imply that these cross-group differences are not statistically distinguishable.

Two points reinforce the interpretation. First, that the response moves only modestly when the Phillips-curve variables are added indicates that the trend shock does not transmit to inflation solely through these contemporaneous channels; a substantial part of its effect operates directly, consistent with the broad-based pass-through documented in the baseline. Second, because the controlled and uncontrolled estimates remain close, the baseline response is not attributable to omitted macroeconomic factors correlated with the estimated trend. The preferred specification nonetheless remains the parsimonious baseline of Equation (4.7), for the post-treatment reason given above; Equation (4.8) serves only to demonstrate robustness.

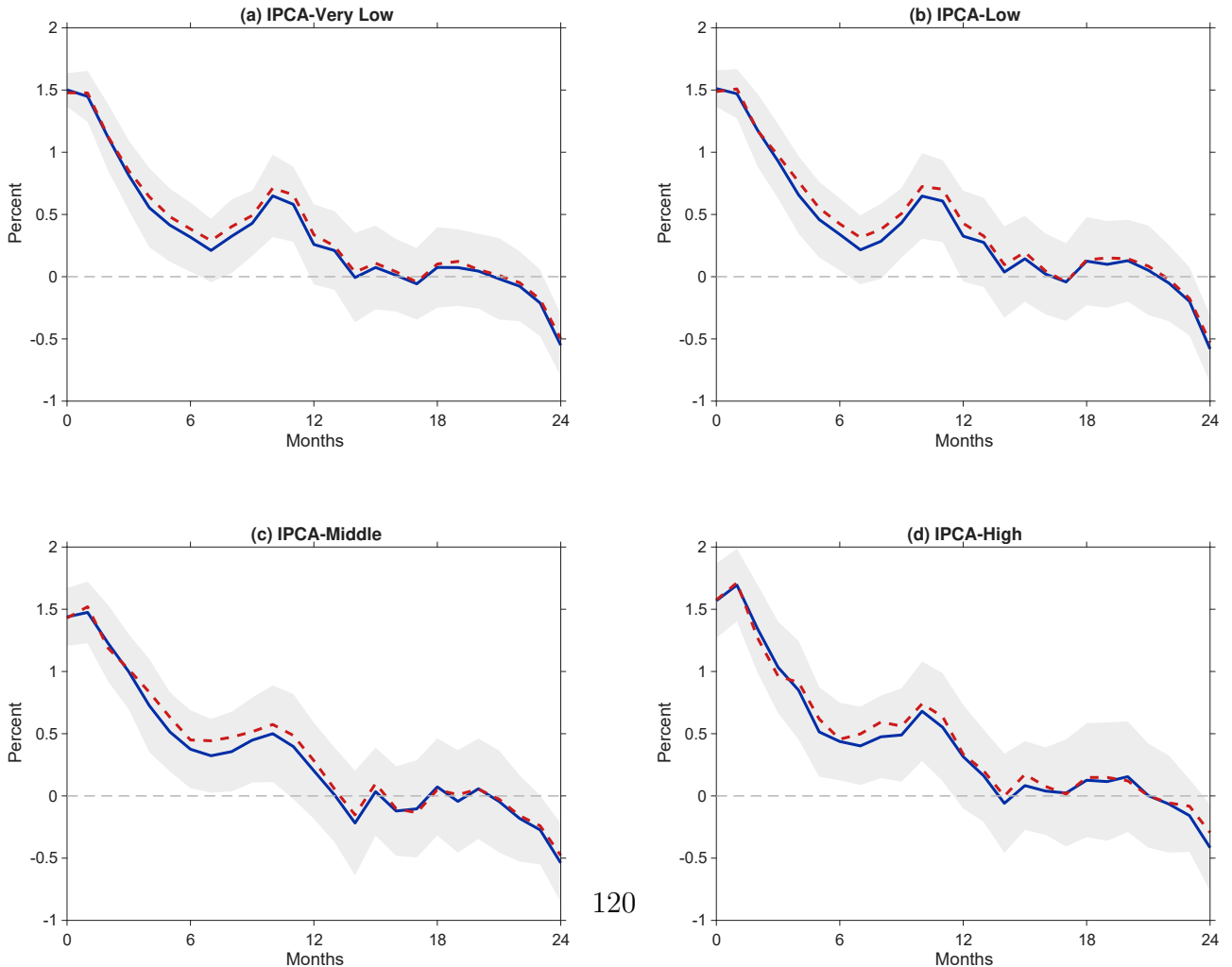
Table 4.12 – Local Projections: Sensitivity to Macroeconomic Controls

Income Group	$h = 12$		$h = 24$	
	Baseline	+ Controls	Baseline	+ Controls
IPCA	0.302 (0.187)	0.384 (0.204)	−0.598 (0.151)	−0.545 (0.155)
Very Low	0.259 (0.164)	0.336 (0.169)	−0.551 (0.127)	−0.498 (0.126)
Low	0.326 (0.186)	0.428 (0.194)	−0.581 (0.138)	−0.529 (0.138)
Middle	0.202 (0.197)	0.283 (0.218)	−0.538 (0.161)	−0.478 (0.168)
High	0.315 (0.212)	0.335 (0.255)	−0.416 (0.178)	−0.295 (0.185)

Notes: Response $\hat{\beta}_h^R$ to a 1 p.p. trend shock. “Baseline” is Equation (4.7); “+ Controls” adds contemporaneous inflation expectations, the output gap (HP) and the exchange rate (Δe). HC3-robust SE in parentheses. Common sample ($t \geq 13$). These controls are post-treatment channels of the trend shock, so the preferred specification omits them; this table is reported only as a sensitivity check. The response is virtually unchanged across the two specifications, with its sign, profile and magnitude preserved at both horizons, confirming that the baseline result is not an artifact of omitted macroeconomic factors.

Figure 4.16 – Local Projections: Baseline vs. Macroeconomic Controls by Income Strata

LP: Baseline vs. + Macro Controls | Level Specification | Common sample $t \geq 13$



5 GENERAL CONCLUSION

The identification of the sources, transmission channels, and distributional consequences of inflation was one of the central questions this thesis set out to address. Aggregate price indices average away a substantial amount of heterogeneity: across the items that compose the consumption basket, across the regions in which prices are formed, and across the households that bear the burden of rising prices. This thesis asked which components of Brazilian inflation were genuinely persistent and which were merely volatile and mean reverting, whether the trajectory of national inflation adequately represented what happened across the country's regions, and whether a single headline number described the price experience of both the poorest and the wealthiest Brazilian households. In an inflation targeting regime such as Brazil's, anchored on the Extended National Consumer Price Index (IPCA) since the 1994 Real Plan, these questions carried direct practical relevance, since the timing, magnitude, and distributional fairness of monetary policy depend on how well the headline index captures the underlying heterogeneity of the price formation process.

To answer these questions, the thesis disaggregated Brazilian inflation along three complementary dimensions, sectoral, regional, and distributional, applying state space methods with stochastic volatility, time varying parameters, and nonlinear convergence tests that allowed permanent and transitory shocks to be separated, allowed persistence to evolve over time rather than being assumed constant, and allowed subgroups of a panel to gravitate toward distinct long run equilibria rather than a single common trend. Each of the three essays applied this set of methods to a different type of disaggregation, sharing a common argument: while an aggregate treatment of Brazilian inflation provides a fundamental baseline, incorporating its internal composition further refined the analysis, thereby optimizing monetary policy decisions and mitigating the social impacts of economic policy.

The first essay analyzed food inflation persistence in Brazil from August 1999 to May 2026 using the Multivariate Core Trend (MCT) model. The results confirmed that food inflation dynamics were structurally heterogeneous: Food at Home exhibited a growing permanent volatility component and a substantially higher outlier probability than Food Away From Home, while Food Away From Home, despite its smaller basket weight, transmitted permanent shocks more intensely to the rest of the system and elicited a stronger Selic response. The permanent volatility of Food at Home switched regime in the post-COVID period, becoming a net transmitter of systemic uncertainty for the first time in the sample, a structural shift that a monetary policy strictly guided by the headline IPCA would have failed to detect in real time. These findings indicated that a uniformly transitory treatment of food shocks based only on the headline index introduced a systematic bias in the assessment of underlying inflation, and motivated the proposal that the Central Bank monitor the posterior outlier probability of Food at Home as an early warning indicator.

The second essay examined inflation persistence and club convergence across eleven Brazilian metropolitan areas from January 2003 to November 2024, combining a Time-Varying Parameter Phillips Curve with a club convergence methodology. The results revealed pronounced heterogeneity in regional persistence, with Curitiba displaying high inertia and Salvador, Belém, and Brasília displaying comparatively low inertia, an asymmetry that the COVID-19 pandemic further accentuated in specific cities. While no global convergence was found for headline regional inflation, disaggregation by sector uncovered strong convergence in Household Items and Transportation, alongside weaker, transitional convergence patterns in Food and Communication. This evidence was consistent with an aggregation bias that concealed substantial subnational inertia behind the national index, and pointed to the need for differentiated regional policy responses rather than a single national diagnostic.

The third essay, published in *The Manchester School*, investigated inflation inequality across four household income strata in Brazil, very low, low, middle, and high income, from July 2006 to April 2025. The results documented a regressive pattern in Brazilian inflation: trend inflation was consistently higher and more volatile for lower income households, whose inflation outliers were also more frequent and more severe, while inflation expectations anchored price setting almost exclusively for the high income group, and the output gap had influenced lower income inflation since 2008, more than a decade before its effect became statistically evident in the headline index. These findings indicated that a uniform monetary policy response calibrated to the aggregate IPCA could systematically arrive too late for the households least able to absorb its costs.

Taken together, the evidence gathered across these three complementary dimensions, sectoral, regional, and distributional, demonstrated that food inflation in Brazil was structurally heterogeneous rather than uniformly transitory, that regional price dynamics combined persistent local inertia with sector specific convergence rather than a single national pattern, and that the burden of inflation fell disproportionately on lower income households through both higher permanent volatility and a more frequent incidence of extreme shocks. Trend inflation, volatility, and persistence were not uniform properties of the Brazilian price system: they varied systematically according to the structure of household consumption, the geography of markets, and the socioeconomic composition of the population, and this variation carried direct implications for the timing and the distributional fairness of monetary policy. An inflation targeting regime anchored solely on the aggregate IPCA therefore risked responding too late, too uniformly, or too regressively to price dynamics that were, in fact, substantially heterogeneous beneath the headline number.

From a policy standpoint, the three essays converged on a common recommendation: the Brazilian Central Bank would benefit from incorporating disaggregated diagnostics, by expenditure category, by region, and by income group, into its regular operational framework, rather than relying exclusively on the aggregate IPCA to gauge the timing and calibration of monetary policy. Doing so would allow policymakers to distinguish transitory disturbances from structural shifts in food prices, to tailor regional strategies to genuinely heterogeneous inertia

patterns, and to recognize that the costs of delayed disinflation are not borne equally across the income distribution.

This thesis was also subject to limitations that open avenues for future research. The MCT framework applied to food inflation did not yet incorporate the physical drivers of agricultural supply shocks, a gap that could be addressed by integrating climate variables directly into the model. The regional analysis suggested that the socio-economic determinants behind heterogeneous persistence patterns warranted further investigation, potentially through weak σ -convergence methodologies. The income inequality analysis relied on a univariate state space approach that evaluated each income stratum in isolation; extending this framework to a multivariate setting, once sufficiently disaggregated sectoral data become available by income group, would allow common macroeconomic shocks to be separated from idiosyncratic, group-specific developments. Pursuing these extensions would further refine the picture of Brazilian inflation heterogeneity developed across the three essays that compose this thesis.