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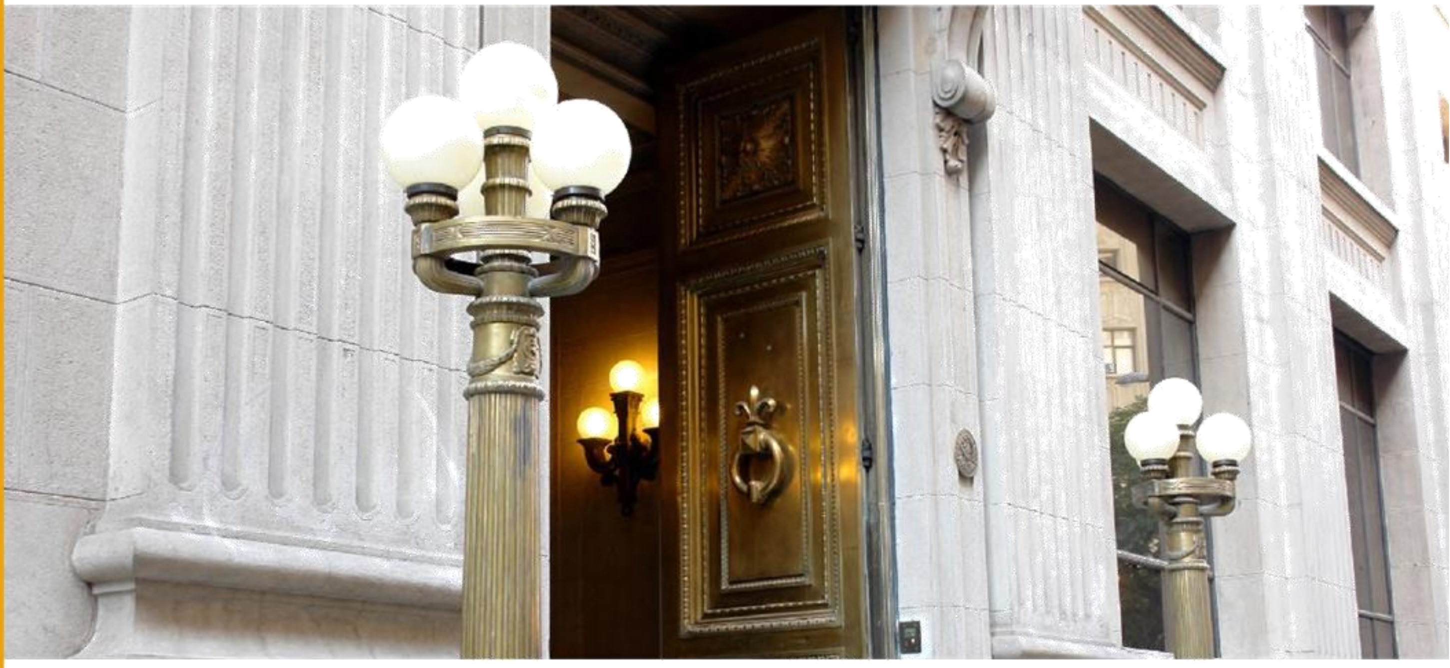

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Exogenous Influences on Long-term Inflation Expectation Deviations: Evidence from Chile[1]

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Resumen
Este artículo examina los determinantes del anclaje de las expectativas de inflación en Chile, tanto dentro como más allá del horizonte de política monetaria de dos años. A pesar de la mayor sensibilidad de las expectativas a la evolución de la inflación efectiva tras el reciente repunte inflacionario, la evidencia de modelos de series temporales lineales y no lineales, así como de análisis de respuesta binaria, sugiere que la confianza en las proyecciones oficiales de inflación del Banco Central puede persistir, incluso frente a influencias exógenas como la incertidumbre de política económica—global y doméstica—y las tensiones geopolíticas. Los resultados indican que, pese a las desviaciones observadas respecto de la meta de inflación, aún puede mantenerse plena confianza en la orientación de la política monetaria. Las pruebas de robustez confirman los resultados de referencia al incorporar el conjunto completo de respuestas de una encuesta de expectativas de inflación ampliamente utilizada. No obstante, los participantes del mercado financiero tienden a anclar sus expectativas con mayor firmeza a la meta, a diferencia de los expertos y académicos, quienes responden más intensamente a la nueva información. Los agentes del sector corporativo parecen situarse entre ambos grupos en la formación de sus expectativas.

Abstract
This article examines the determinants of the anchoring of inflation expectations in Chile, both within and beyond the two-year policy horizon. Despite the heightened sensitivity of expectations to actual inflation developments following the recent inflation surge, evidence from linear and non-linear time-series models, as well as binary-outcome analyses, suggests that confidence in the Central Bank's official inflation forecasts can persist, even in the presence of exogenous influences such as global and domestic economic policy uncertainty and geopolitical tensions. The findings indicate that, notwithstanding observed deviations from the inflation target, full confidence in the monetary policy stance can be maintained. Robustness checks confirm the baseline results when incorporating the full set of responses from the widely used inflation expectations survey. Nonetheless, financial market participants tend to anchor their expectations more firmly to the target, in contrast to experts and academics, who respond more strongly to new data. Members of the corporate sector appear to lie between these two groups in their expectations behaviour.

[1] I am grateful to Lucas Bertinatto, Raimundo Contreras, Benjamín García, Felipe Guzmán, Markus Kirchner, Michael Pedersen, and Javier Turén, as well as to seminar participants at the Central Bank of Chile, the 5th Doctoral Workshop at the Pontifical Catholic University of Chile, and the 2025 Annual Meeting of the Chilean Economic Society (SECHI), for helpful comments and suggestions. Any remaining errors or omissions are the sole responsibility of the author. The views expressed are those of the author and do not necessarily reflect the views of the Central Bank of Chile or its Board Members.

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1 Introduction

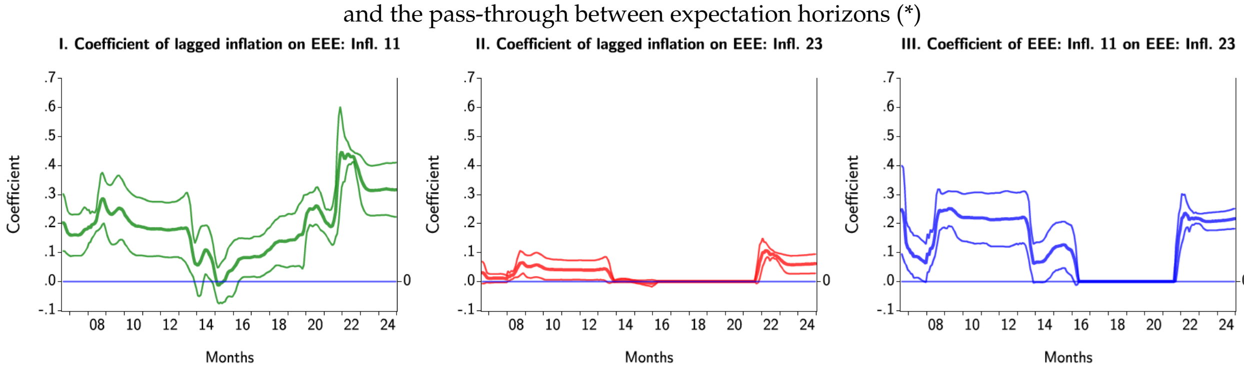
Inflation expectations' anchoring is defined as the ability of monetary authorities to influence the public's inflation expectations (King, 2005), typically towards a widely recognised, headline-based inflation target within a specified timeframe. The benefits of anchoring expectations within an inflation-targeting regime are patent in terms of enhanced price stability (Christiano and Gust, 2000; Levin, Natalucci, and Piger, 2004; Mishkin, 2007) and reduced output volatility (Mishkin and Schmidt-Hebbel, 2002, 2007; Fatás, Mihov, and Rose, 2007).

An operational definition of anchoring equates to a "disconnection" between actual and expected inflation, with expectations instead aligning with (or being *close* to) the target (Van der Cruijsen and Demertzis, 2011; Ehrmann, 2015), remaining insulated from actual inflation developments. As Bernanke (2007) states, anchoring implies that long-run inflation expectations are "*relatively insensitive to incoming data*."

Through reduced-form econometric estimations, using the case of Chile as an example, this article aims to: (i) analyse the extent to which measures of expectations at different horizons are disconnected from actual inflation developments within the policy horizon (*i.e.*, two years ahead); and (ii) conditional on (i), examine whether long-term deviations from the target, beyond the policy horizon, respond to the Central Bank of Chile's (BCCh) policy actions and/or to exogenous factors, such as measures of economic policy uncertainty and geopolitical tensions.

The first hypothesis is supported by the surge in global inflation and persistence caused by the COVID-19 pandemic, updating the previous evidence presented in Medel (2018) for Chile. As suggested by Ehrmann (2015), the pass-through from actual to expected inflation should be minimal if expectations are anchored.[1] Similarly, long-run anchored expectations should not systematically react to short-run developments (Dräger and Lamla, 2013). Rolling estimates in Figure 1 indicate that, while generally stable, the ongoing rise in inflation expectations exhibits greater sensitivity to actual data compared to the previous markedly inflationary episode (*i.e.*, the *Global Financial Crisis* of 2008–09) (see panels I and II). Additionally, although relatively moderate, the pass-through from short- to long-run expectations has also increased since mid-2020 (see panel III). These facts call for an updated review of the state of expectations anchoring within the policy horizon and beyond.

Figure 1. Rolling-window coefficients of actual inflation on inflation expectations
and the pass-through between expectation horizons (*)



(*) Panels I and II depict the Ordinary Least Squares rolling estimates of the β parameter from the regression $\pi^{EEE}_{t|t+h} = \alpha + \beta\pi_{t-1} + \varepsilon_t$, where $\pi^{EEE}_{t|t+h}$ represents the BCCh's *Economic Expectations Survey* median responses for inflation expectations h=11 and h=23 months ahead, respectively (α is a constant term and ε_t is an error term). Panel III presents the rolling estimates of the γ parameter from the regression $\pi^{EEE}_{t|t+23} = \mu + \gamma\pi^{EEE}_{t|t+11} + \nu_t$ (μ is a constant term and ν_t is an error term). Initial estimation sample: 2001.9–2006.8 (60 observations; monthly estimates). Full sample: 2001.9–2024.12 (280 observations). Confidence intervals: $\pm$2 standard deviations. Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

[1] Particularly, Ehrmann (2015) defines *operational* anchoring as a state in which expected inflation remains closely tied to the Central Bank's target, regardless of actual inflation movements.

The second hypothesis applies because Chilean survey-based expectations data extend only to the policy horizon.[2] Analyses beyond the two-year horizon must therefore rely on estimates of inflation expectations. Drawing on Demertzis, Marcellino, and Viegi (2008), I derive a long-run, steady-state inflation expectation and examine the determinants of its deviation from the 3% target. It is important to notice that, as anchoring results from policy actions, a mere deviation from the target does not necessarily imply *de-anchoring* of expectations. Instead, fundamentals and shocks may interact in ways that push expectations away from the target without undermining confidence in official Central Bank forecast.[3] Accordingly, I provide both time-series (linear and non-linear) and binary-outcome model-based evidence, showing that in steady state, deviations from the target are yet influenced not only by Central Bank forecasts but also by measures of exogenous economic policy uncertainty. Indeed, the results suggest that a Chile-specific version of the Baker, Bloom, and Davis (2016)'s *Economic Policy Uncertainty Index* (EPU) as well as a principal component including an *Economic Uncertainty Index* and geopolitical tensions, influences deviations from the target even when controlling for other prospective statistical information published by the Central Bank.

The results of the analysis conducted in this article suggest that, during the most recent inflation surge, the sensitivity of expectations to actual inflation increases both at the 11-month-ahead horizon and at the longest-term horizon. Nevertheless, both the official short-term inflation forecast from the BCCh and the target itself account for most of the explanation of the 11-month-ahead forecast, rather than actual inflation, suggesting anchoring of expectations. At the policy horizon, actual inflation plays virtually no role. These findings are confirmed by impulse response estimations from a simple bivariate VAR including actual and expected inflation.

At the longest-term horizon, time-series models suggest that both the forecasting error and the deviation of the official BCCh forecast are robustly statistically significant. Notably, uncertainty also plays a role in explaining steady-state deviations of expectations from the target. These results are further supported by simple switching regressions, in which a regime characterised by higher uncertainty and heightened geopolitical tensions displays statistically significant results for uncertainty measures. Disregarding the memory and persistence of the analysed variables, binary-outcome models are employed. Probit estimates confirm that, in steady state, both official BCCh forecasts and uncertainty robustly contribute to deviations in expectations. These findings underscore that, despite deviations from the target, confidence in predictive information provided by the BCCh can still be fully maintained. Further exercises confirm the baseline results when using all responses from the inflation expectations survey. In fact, financial market participants tend to be more inclined to strictly anchor their expectations to the target, in contrast to experts and academics, who are more reactive to incoming data. In turn, respondents from the corporate sector are in between, being less reactive to new data while also being less anchored than financial market participants.

The next section provides a brief literature review to better situate the exercise conducted in this study. The core of the paper is presented in section 3, which focuses on the econometric strategy and results. This section first describes the data before using it to conduct various time-series analyses and estimations on the determinants of long-run, steady-state deviations of expected inflation from the target. These estimations include both linear and non-linear approaches, with the latter relying on simple switching regressions. The analysis is further complemented by binary-outcome estimations, which disregard the persistence of the series and treat deviation episodes as isolated events. This is followed by Section 4, which presents further exercises, assessing the stability of the previous estimates over time and disentangling the sources of reported inflation expectations among experts, financial market participants, and corporate sector respondents. The paper concludes with Section 5.

[2] Note that it was only in 2019.11 that Chile's most widely used and longest-running survey of inflation expectations—the *Economic Expectations Survey* (EEE), conducted by the Central Bank of Chile (BCCh) since 2000.2—began to include a question on 35-month-ahead inflation expectations (whereas the BCCh's policy horizon is 24 months ahead). The expected inflation for the 35-month horizon has consistently aligned with the 3.0% target, except in 2022.1, when it registered 3.1%.

[3] This may represent a particular case of a Central Bank that enjoys high public confidence following years of effective communication, policy discipline, and market feedback regarding the monetary policy framework. Moreover, in this context, major long-run deviations from the inflation target are infrequent and readily explainable. Notice that, this may not necessarily be the case for the majority of central banks operating under an inflation-targeting regime.

2 Literature review

A growing body of literature has explored the formation and (de)anchoring of inflation expectations in response to uncertainty, monetary shocks, and Central Bank communication. Adrian (2023) offers an updated discussion on the topic, providing a conceptual synthesis that frames expectations as a core transmission channel of monetary policy.

In relation to the role of uncertainty, Istrefi and Piloiu (2014) employ a panel VAR framework covering several advanced economies and find that shocks to EPU produce a persistent downward adjustment in inflation expectations. Their results suggest that uncertainty operates as a disinflationary force, particularly when monetary policy credibility is stable. Similarly, Rooj, Banerjee, and Sengupta (2025) analyse Indian household survey data using cross-sectional regressions, uncovering that responses to EPU shocks are highly heterogeneous across demographic groups. They show that education level, income, and urban/rural location systematically shape the way individuals revise their expectations in the face of rising uncertainty, given a role to perceived inflation and inflation literacy.

Binder (2017) develops a novel method for measuring subjective inflation uncertainty based on the extent of rounding in individual survey responses. This rounding-based metric is shown to correlate strongly with standard macroeconomic and policy-related uncertainty indices. Her approach highlights that greater uncertainty leads respondents to provide coarser forecasts, thereby offering a micro-founded and behaviourally grounded indicator of inflation uncertainty. In a complementary direction, Silva and Araújo (2023) introduce a perception-based measure of uncertainty derived from textual analysis of Central Bank communication. Using the COVID-19 pandemic as an exogenous shock, they demonstrate that more negative or ambiguous language in monetary policy communication significantly increases inflation expectations, particularly during periods of heightened crisis sensitivity. Using an alternative measure of uncertainty, they find that it plays a role in shaping inflation expectations, which—depending on the size and perception of the shock—may also influence longer-term expectations.

Several studies also examine theoretical implications of unanchoring. Gáti (2023) develops a New Keynesian model with endogenous learning gains, showing how expectation dynamics modify optimal policy responses under unanchoring. Bonomo *et al*. (2024) use Brazilian high-frequency forecast data to document long-run de-anchoring following a surprise policy reversal, supported by a learning model calibrated to microdata. Likewise, Gobbi, Mazzocchi, and Tamborini (2019) incorporate regime-switching beliefs into a New Keynesian framework, illustrating the feedback loop between output, belief probabilities, and the effectiveness of monetary policy under self-fulfilling de-anchoring. Together, these contributions emphasise the multi-dimensional and dynamic nature of inflation expectation formation, particularly in environments characterised by uncertainty and evolving policy credibility.

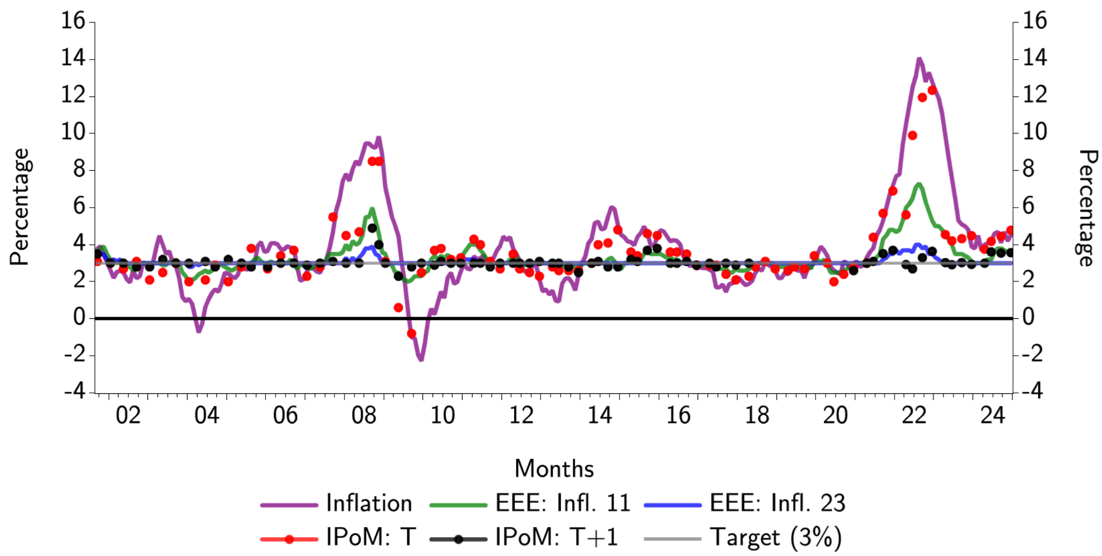
Chile provides an insightful case study, given its well-established inflation-targeting framework since 2000.9–a pioneering initiative among emerging market economies–and its unique exposure to global economic shocks (Central Bank of Chile, 2020). As such, several papers have emphasised the benefits that expectations anchoring has brought to the Chilean economy since the implementation of the fully-fledged inflation-targeting regime; see, for instance, Gürkaynak *et al*. (2007), De Pooter *et al*. (2014), and Arias and Kirchner (2019). Pierdzioch and Rülke (2013) provide early evidence suggesting that inflation expectations in Chile are not fully anchored, as professional forecasters tend to adjust their projections in response to inflation surprises. Medel (2018) confirms this pattern, showing that inflation expectations remain sensitive to short-term deviations and that anchoring varies across forecast horizons. Pedersen (2015) extends this view by demonstrating that central bank forecasts influence private expectations, yet the strength of this influence depends on forecast uncertainty and the timing of releases. More recent findings by Pedersen (2024, 2025) indicate that financial traders' expectations respond asymmetrically to monetary policy surprises, with the degree of responsiveness depending on the level of disagreement among agents and the prevailing inflation environment. Additionally, Feldkircher and Siklos (2019) show that external shocks, such as oil price fluctuations, significantly affect inflation expectations in emerging economies, including Chile. Altogether, these studies suggest that while the Chilean inflation-targeting regime has contributed to a more stable expectations framework, full anchoring remains contingent on credible communication, macroeconomic stability, and global conditions. The contribution of this article lies in the notion that it is possible to diverge from the inflation target in the long run while maintaining full confidence in official Central Bank inflation forecasts, which interact with exogenous factors beyond the control of policymakers.

3 Econometric strategy and results

3.1 Data

Official inflation data are compiled monthly by the Chile's National Statistics Institute (INE) and comprise five linked-chain consumer baskets (2008, 2009, 2013, 2018, and 2023). Inflation expectations for 11- and 23-months horizons are sourced from the *Economic Expectations Survey* (EEE), labelled as $\pi^{EEE}_{t|t+11}$ and $\pi^{EEE}_{t|t+23}$, conducted monthly by the BCCh since 2001.9, while BCCh's inflation forecasts are published quarterly since 2008 (three times per year since 2000) in its Monetary Policy Reports (in Spanish, *Informe de Política Monetaria* or IPoM). IPoM's forecasts are available up to December of the current year (π^{IPoM}_{T}) and December of the following year (π^{IPoM}_{T+1}).[4] The usable sample spans from 2001.9 to 2024.12 (280 observations). All series are stationary according to the Phillips and Perron (1988) test. The time series are presented in Figure 2, with descriptive statistics provided in Table A1 in Annex A.

Figure 2: Time series of actual inflation, publicly expected inflation, BCCh's forecasts, and the inflation target (*)



(*) All series are expressed as percentages, representing the year-on-year variation of the Consumer Price Index (CPI). Usable sample span: 2001.9-2024.12 (280 observations). Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

3.1.1 Inflation expectations beyond the policy horizon

Since the determinants of deviations in inflation expectations over the longest horizons are being analysed, it is essential to have an appropriate measure of them. Demertzis, Marcellino, and Viegi (2008, 2009) assume a bivariate VAR model that includes both expected and actual inflation:

$$\begin{bmatrix} \pi_t \\ \pi^{EEE}_{t|t+h} \end{bmatrix} = \begin{bmatrix} a_0 \\ c_0 \end{bmatrix} + \begin{bmatrix} a(L) & b(L) \\ c(L) & d(L) \end{bmatrix} \begin{bmatrix} \pi_{t-p_\pi} \\ \pi^{EEE}_{t-p_\pi|t+h} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \tag{1}$$

where a_0 and c_0 are intercepts; $a(L)$, $b(L)$, $c(L)$, and $d(L)$ are polynomials containing the coefficients of the lagged variables, L is a backshift operator, working as $L^j x_t = x_{t-j}$; $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are white noises terms, and $h = 11$. The

[4] Note that "T" and "$T+1$" represent the horizons "*December of the current year*" and "*December of the next year*," respectively, which differ from "$t+h$," as measured in traditional monthly time-series units. This implies that these series have missing values across the t-dimension.

coefficients of each polynomial $\theta(L)$, with $\Theta = \{a(\cdot), b(\cdot), c(\cdot), d(\cdot)\}$, are denoted by θ_1, θ_2, ..., θ_{p_θ}, where p_θ is the lag length chosen as a block, *i.e.*, p_a=p_b=p_c=p_d. The long-run solution of equation (1) in the stationary form, $\Pi_t = \Theta\Pi_{t-p_\theta}$, where $\Pi_t = \Pi_{t-p_\theta}$, for all p_θ, is given by:

$$\begin{aligned} \pi &= \frac{a_0}{1-a_1-\ldots-a_{p_a}} + \frac{b_1+\ldots+b_{p_b}}{1-a_1-\ldots-a_{p_a}}\pi^{EEE}, \\ \pi^{EEE} &= \frac{c_0}{1-d_1-\ldots-d_{p_d}} + \frac{c_1+\ldots+c_{p_c}}{1-d_1-\ldots-d_{p_d}}\pi. \end{aligned} \tag{2}$$

Under this framework, anchoring is based on Bomfim and Rudebusch (2000) by defining expected inflation as a weighted average of the inflation target (π^*, now a parameter to be inferred) and lagged inflation, becoming $\pi^{EEE}_{t|t+h} = \omega\pi^* + (1-\omega)\pi_{t-1}$. The parameter $0 \leq \omega \leq 1$ measures the degree to which expectations are anchored; ω=1 indicates perfect anchoring to π^*. By comparing the second equation (2) with $\pi^{EEE}_{t|t+h} = \omega\pi^* + (1-\omega)\pi_{t-1}$, I derive the time-fixed components:

$$\omega\pi^* = \frac{c_0}{1-d_1-\ldots-d_{p_d}}, \quad (1-\omega) = \frac{c_1+\ldots+c_{p_c}}{1-d_1-\ldots-d_{p_d}}, \tag{3}$$

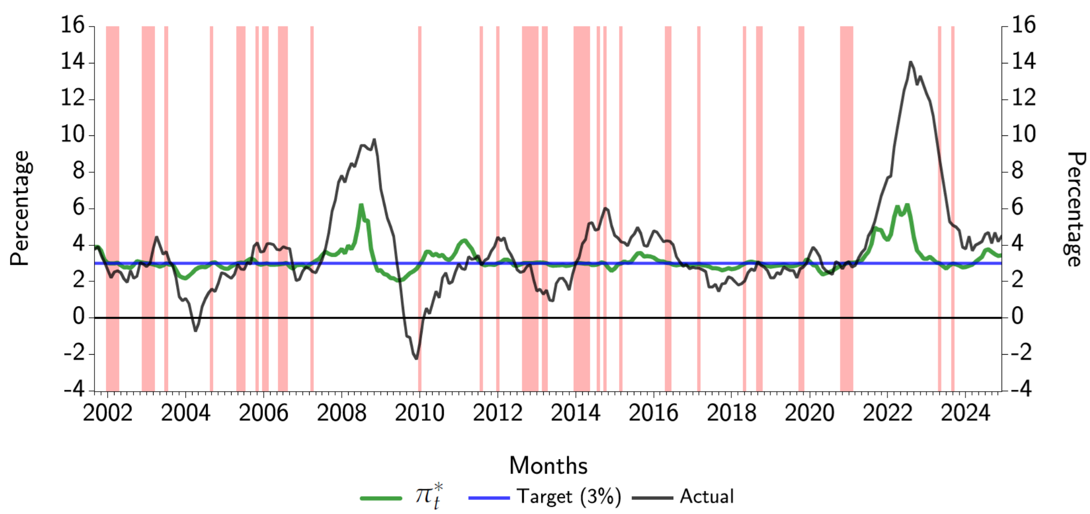
and hence, the solution for π^* and the weight in the formation of inflation expectations (ω), as a function of the parameters, is given by:

$$\pi^* = \frac{c_0}{1-d_1-\ldots-d_{p_d}-c_1-\ldots-c_{p_c}}, \quad \omega = 1 - \frac{c_1+\ldots+c_{p_c}}{1-d_1-\ldots-d_{p_d}}. \tag{4}$$

Notice that considering a time-varying parameter VAR(1) version from equation (1) (*i.e.*, $\{a_{0t}, a_t, b_t, c_{0t}, c_t, d_t\}$), it becomes possible to obtain time-varying estimates of π^* and ω. The former, π^*_t, represents a steady-state measure of inflation expectations, which will be further analysed, while the latter represents the weight assigned to a fixed target, and with $(1-\omega)$ representing the weight given to current inflation developments.

All time-varying coefficients are estimated using the Kalman filter and are assumed to follow a random walk process. Initial parameter calibration is based on an Ordinary Least Squares estimation using the pre-inflation surge sample (2001.9 to 2020.3). Both error terms are assumed to be independent of each other (Demertzis, Marcellino, and Viegi, 2008, 2009). The results of π^*_t estimates are presented in Figure 3, highlighting two episodes of deviations: the 2008–09 *Global Financial Crisis* and the COVID-19 pandemic.

Figure 3: Time series of actual inflation, target inflation, and steady-state inflation expectations estimates (*)



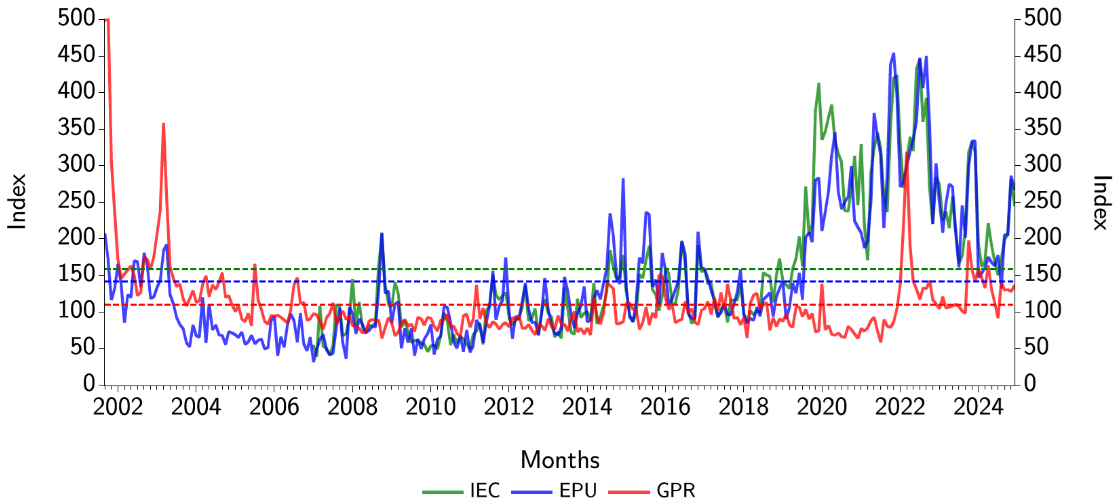
(*) All series are expressed as percentages. Shaded bars: Steady-state inflation expectations = inflation target (3%). Usable sample span: 2001.9-2024.12 (280 observations). Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

3.1.2 Uncertainty and geopolitical tensions measures

To analyse the influence of exogenous factors on deviations of steady-state inflation expectations from the target, I employ two Chile-specific measures of uncertainty alongside a measure of global geopolitical tensions. The purpose of incorporating these variables into the analysis is to assess their significance and interaction with official prospective information published by the BCCh. Key characteristics of these measures is their exogeneity and potential real-economy impact. As they are based on economic news (both domestic and global), they capture the intensity of developments and shocks with non-negligible real-economy impacts.[5] Their dynamics, particularly during peak episodes, represent events that are not generated by, and/or lie beyond the control of, domestic monetary authorities. The uncertainty measures used are the *Economic Uncertainty Index* (IEC) and the *Economic Policy Uncertainty Index* (EPU).[6]

The series of geopolitical tensions used in this analysis is the *Geopolitical Risk Index* (GPR), developed by Caldara and Iacoviello (2022). This index quantifies adverse geopolitical events and associated risks based on a tally of newspaper articles covering geopolitical tensions. Elevated geopolitical risk is linked to a greater probability of economic crises and increased downside risks to the global economy (see Caldara and Iacoviello, 2022, for details). The time series plot of the three indices is presented in Figure 4, along with its descriptive statistics in Table A1.

Figure 4: Time series of IEC, EPU, and GPR (*)



(*) All series are expressed as 100-base indices: IEC: 100=2007.1-2016.10 average, EPU: 100=1993.1-2016.10 average, and GPR: 100=1985.1-2019.12 average. Usable sample span: IEC: 2007.1-2024.12 (216 observations), and EPU and GPR: 2001.9-2024.12 (280 observations). Horizontal lines = sample mean of each series. Sources: Centre for Economic and Social Policies (CLAPES UC; Cerda, Silva, and Valente, 2017) and Caldara and Iacoviello (2022) (data retrieved from https://www.MatteoIacoviello.com/GPR.htm).

3.2 Time-series models' evidence

3.2.1 Empirical evidence within the policy horizon

A first set of results examines whether there is evidence of expectations anchoring within the policy horizon. While various tests exist, this article employs first one that combines two informational devices set by the Central Bank—

[5]See Carrière-Swallow and Medel (2011) and Cerda, Silva, and Valente (2017) for estimates of the impact of uncertainty shocks on disaggregated demand in the case of Chile.

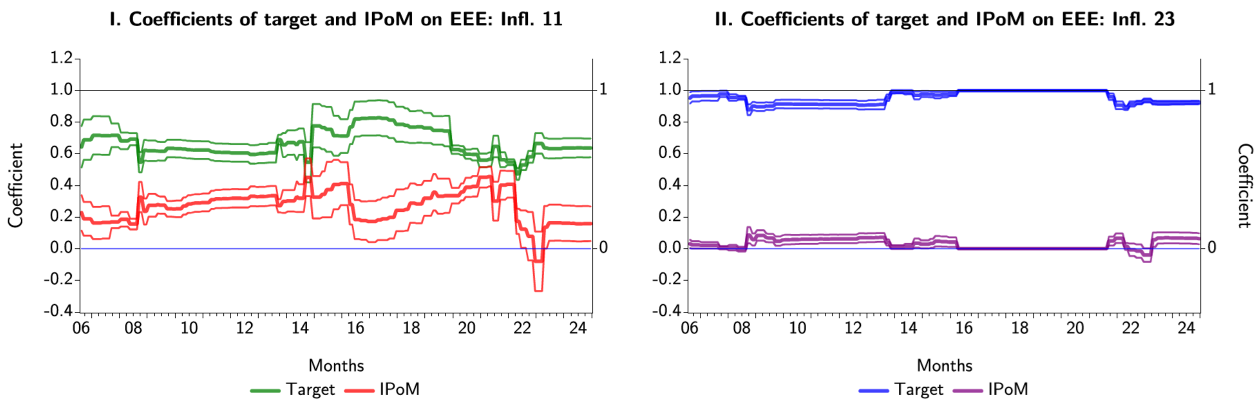
[6]The construction of the EPU follows the methodology of Baker, Bloom, and Davis (2016), which involves a scaled count of specific terms related to *uncertainty* and *economics* in news articles from the oldest and most widely circulated newspaper in Chile (see Cerda, Silva, and Valente, 2017, for further details). The IEC, in turn, follows the EPU methodology but incorporates a broader newspaper coverage and a wider set of keywords. Consequently, the authors termed the resulting index as "economic uncertainty", as it is not limited solely to "economic policy uncertainty" (see Cerda, Silva, and Valente, 2016, for further details). The time series plot of these indices is presented in Figure 4, and their descriptive statistics are shown in Table A1.

the inflation target and the forecasts from the IPoM—along with actual inflation.[7] Thus, I analyse a weighting regression following Łyziak and Paloviita (2017):

$$\pi^{EEE}_{t|t+h} = \lambda^{Target}\pi^{Target}_t + \lambda^{IPoM}\pi^{IPoM}_T + (1 - \lambda^{Target} - \lambda^{IPoM})\pi_{t-1} + \varsigma_t, \tag{5}$$

where π^{IPoM}_T is the inflation forecast made by the BCCh for December of the current year, ς_t is an error term, and λ^{Target} and λ^{IPoM} are coefficients to be estimated. The rolling estimates of the weights are presented in Figure 5. The results suggest that at the 11-month horizon, the weights remain relatively stable, with the bulk of volatility concentrated during the pandemic period. While the target coefficient exhibits values within the range of previously observed estimates, this is not the case for IPoM forecasts. Interestingly, between 2022.9 and 2023.4, the IPoM coefficient displayed a negative value, albeit not statistically significant, indicating a limited role for actual inflation. This is possible because the parameters are not constrained to sum to unity but can be interpreted as weights. This episode indicates a different assessment by EEE respondents regarding current and forecasted inflation from the BCCh, assigning a relatively higher weight to current inflation (12.23% average during this period) rather than to the IPoM forecast (9.61% average during this period). However, it is worth noting that a similar dynamic is observed at the 23-month horizon, albeit to a much lesser extent. At this horizon, as the weight on the inflation target remains close to unity, EEE respondents acknowledge that monetary policy remains capable of accommodating such a shock and steering inflation towards the target within the policy horizon. This provides evidence of inflation expectations anchoring at the policy horizon.

Figure 5: Rolling-window coefficients of inflation target and IPoM inflation forecasts on inflation expectations (*)



(*) Panels I and II depict the Ordinary Least Squares rolling estimates of the λ^{Target} and λ^{IPoM} parameters from the regression of equation (5). Initial estimation sample: 2001.9–2006.8 (60 observations; monthly estimates). Parameter $\lambda^{\pi} = 1 - \lambda^{Target} - \lambda^{IPoM}$ not shown. Full sample: 2001.9–2024.12 (280 observations). Confidence intervals: ± 2 standard deviations. Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

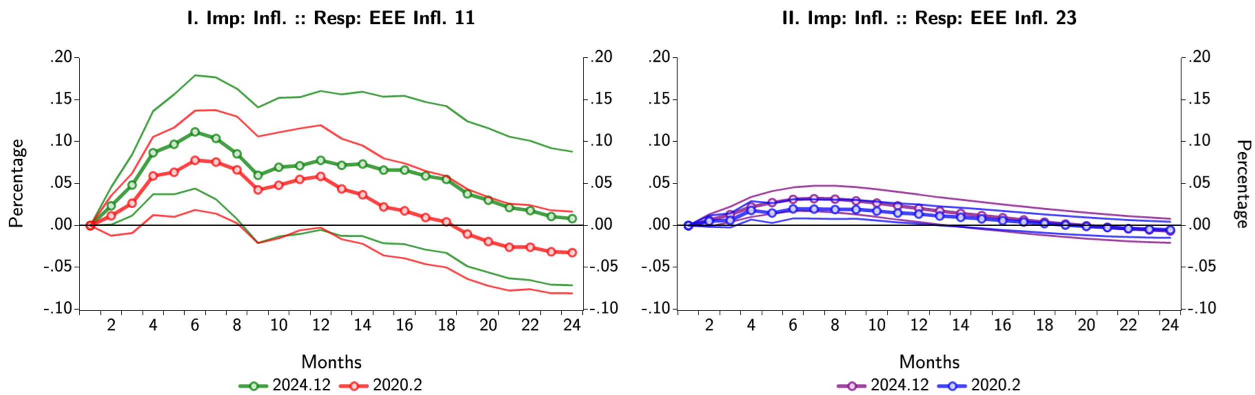
A second set of results is based on a comparative statics analysis of the impulse response functions derived from the estimates of equation (1)—specifically, the response of expectations to a one-standard-deviation shock in actual inflation. To this end, the VAR specification of equation (1) is estimated with fixed coefficients using two samples: (i) 2001.9–2020.2 (pre-COVID-19 sample), and (ii) 2001.9–2024.12 (full sample).[8] The results are presented in Figure 6. While the dynamics are qualitatively similar across both samples, an interesting finding emerges at the 11-month horizon, where full-sample estimates are consistently higher than those from the pre-COVID-19 sample. This suggests that expectations have become more sensitive to actual inflation, peaking six months after the shock

[7] Pedersen (2015) shows that IPoM forecasts indeed influence EEE survey responses in the short run, whereas the evidence is weaker for medium-term predictions.

[8] For both samples and both horizons, the order of the VAR(p) is selected based on the Akaike Information Criterion. This results in p=11 and p=12 for $\pi^{EEE}_{t|t+11}$ in the shortened and full sample, respectively, and p=6 and p=12 for $\pi^{EEE}_{t|t+23}$ for the same horizons. Thus, the greater volatility in the $\pi^{EEE}_{t|t+23}$ series necessitates incorporating more information for its modelling.

and gradually dissipating within 24 periods (compared to 18 periods in the shortened sample). Nevertheless, these estimates never exceed 12%, aligning with the instantaneous effects reported in Figure 1. At the policy horizon, the response of expectations stays muted, with a peak of 0.03% in the seventh period. This finding reinforces the earlier conclusion that expectations at the policy horizon are shaped primarily by the prospective information published by the Central Bank, rather than by actual inflation outcomes.

Figure 6: Impulse response function estimates for a one-standard-deviation shock in actual inflation and response of expected inflation (*)



(*) Impulse response to Cholesky one-standard-deviation innovations (adjusted for degrees of freedom). The 95% confidence intervals are computed using Monte Carlo standard errors with 5000 replications. "2024.12" refers to the full sample (2001.9–2024.12; 280 observations), and "2020.2" refers to the pre-COVID-19 sample (2001.9–2020.2; 222 observations). Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

3.2.2 Empirical evidence beyond the policy horizon

A first set of results beyond the policy horizon pertains to modelling the π_t^* series using time series models, incorporating variables set or strongly influenced by the BCCh, while also examining the potential role of exogenous indices in explaining steady-state deviations from the target. The following variables are added to the existing set using similar regressors as in Pedersen (2015) to analyse the influence of the IPoM on EEE inflation forecasts:

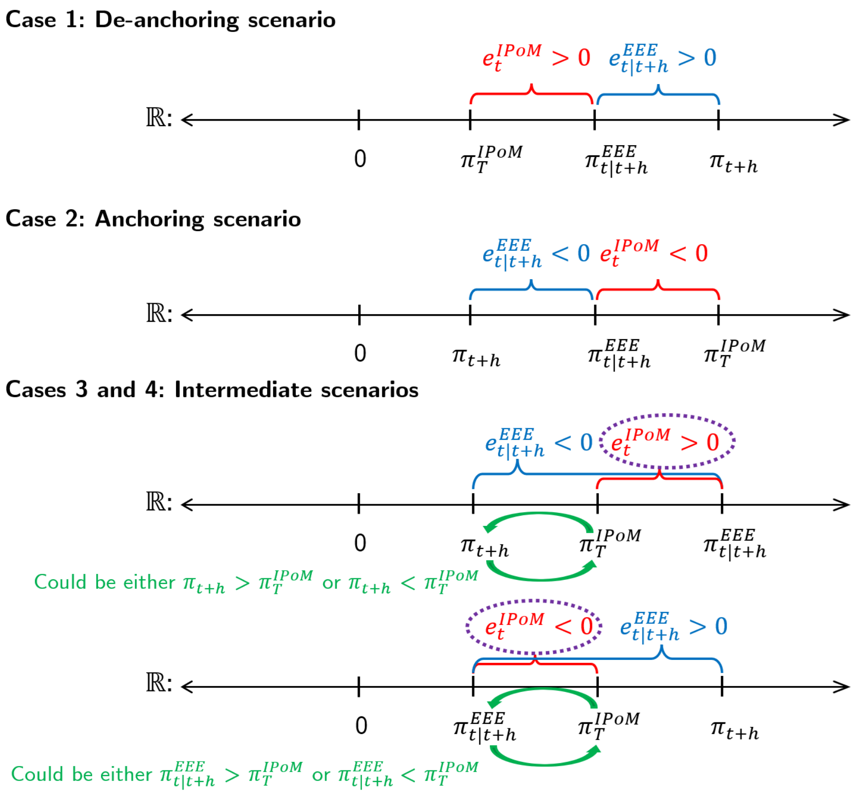
- e_t^{Target}: Constructed as the difference between the inflation target ($\overline{\pi} = 3\%$) and actual inflation, thus $e_t^{Target} = (\pi_t - \overline{\pi})$. A positive coefficient associated with e_t^{Target} is directly linked to a long-term deviation. In this context, the variable accounts for the level of current inflation,
- $e_{t|t+h}^{EEE}$: Constructed as the forecasting error for horizon h with $h = 11$ and $h = 23$, thus $e_{t|t+h}^{EEE} = (\pi_{t+h} - \pi_{t|t+h}^{EEE})$ could be termed also as *unconditional inflation surprise*. A positive coefficient associated with $e_{t|t+h}^{EEE}$ implies that agents take their forecasting errors into account when formulating new forecasts, following an adjustment mechanism based on learning. Thus, if inflation exceeds expectations, the probability of deviating from steady-state expectations increases, whereas the opposite occurs when agents overpredict,
- $e_{t|T}^{IPoM}$: Constructed as the difference between the EEE forecast at 11-month horizon $\pi_{t|t+11}^{EEE}$ and the IPoM forecast π_T^{IPoM}, thus $e_{t|T}^{IPoM} = (\pi_{t|t+11}^{EEE} - \pi_T^{IPoM})$, could be termed as *conditional forecast surprise*. A positive coefficient associated with $e_{t|T}^{IPoM}$ suggests that the probability of deviating from steady-state expectations increases if the EEE forecast exceeds that of IPoM. While this may seem intuitive, it should be interpreted in conjunction with the $e_{t|t+h}^{EEE}$ coefficient.

The rationale behind these regressors is illustrated in Figure 7. The interaction between these two regressors generates four distinct cases of expectations deviations if both coefficients are positive.

The first case (Case 1 in Figure 7) represents pure de-anchoring, where both error-based regressors are positive. This indicates that official forecasts deviate significantly from actual inflation (excessively underestimating inflation), with the EEE forecast positioned between the official forecast and actual inflation. In this scenario, the precision of the IPoM forecast is inaccurate, and with actual inflation exceeding both forecasts, EEE respondents lose confidence in the IPoM forecast and adjust their own forecasts upward, bringing them closer to actual inflation. As a result, the EEE forecast remains consistently more accurate than the IPoM forecast, inevitably increasing the probability of steady-state expectations deviating from the target. Within the usable sample, this situation occurs in 13% of total observations.

A second case (Case 2 in Figure 7) represents pure anchoring, where both error-based regressors are negative. This indicates that the BCCh forecast also deviates significantly from actual inflation, but this time by overpredicting it. As a result, $\pi^{EEE}_{t|t+h}$ is again positioned between π_{t+h} and π^{IPoM}_{T}, but with a strong bias towards the lower figure, *i.e.*, π_{t+h}. This causes inflation expectations to move closer to the target, which is also the case for π^{IPoM}_{T}, and anchoring expectations. Within the usable sample, this situation occurs in 10% of total observations.

Figure 7: Economic rationale of $e^{EEE}_{t|t+h}$ and e^{IPoM}_{T} regressors in relation to $\pi^{EEE}_{t|t+h}$, π^{IPoM}_{T}, and π_{t+h} (*)



(*) Source: Author's calculations.

Finally, two intermediate cases arise: (i) when $\pi^{EEE}_{t|t+h}$ is higher than both π^{IPoM}_{T} and π_{t+h}, but no comparison is made between π^{IPoM}_{T} and π_{t+h} (Case 3 in Figure 7), and (ii) when π_{t+h} is higher than both $\pi^{EEE}_{t|t+h}$ and π^{IPoM}_{T}, but no comparison is made between $\pi^{EEE}_{t|t+h}$ and π^{IPoM}_{T} (Case 4 in Figure 7). In these cases, the direction of expectation deviations in the steady state is determined by the sign of the $e^{IPoM}_{t|T}$ variable in conjunction with the $e^{EEE}_{t|t+h}$ variable. This implies that, despite the positive coefficients associated with both $e^{EEE}_{t|t+h}$ and $e^{IPoM}_{t|T}$, the lasting effect of anchoring or de-anchoring depends on the relative position of $\pi^{EEE}_{t|t+h}$ with respect to π^{IPoM}_{T}. Notably, if $\pi^{EEE}_{t|t+h}$ is required to adjust towards π_{t+h} when the latter is lower than π^{IPoM}_{T}, then it reinforces anchoring. Specifically, if $\pi^{EEE}_{t|t+h}$ lies between π_{t+h} and π^{IPoM}_{T}, it will shift towards π_{t+h} in pursuit of accuracy. If, coincidentally, π_{t+h} is lower than π^{IPoM}_{T}, this movement will unequivocally lead to anchoring. However, EEE respondents are at least as forward-looking as the Central Bank and thus form their expectations by weighting both π_{t+h} and π^{IPoM}_{T}, plus some degree of uncertainty in other macroeconomic variables that may help to frame their inflation forecast. In this framework, as mentioned above, if π^{IPoM}_{T} is positioned significantly away from π_{t+h}, the weight assigned to it by EEE respondents will tend towards zero.

These two weighting cases, however, are challenging to fully capture within a linear classical regression framework, where coefficients are interpreted under the assumption that all other variables remain constant. Notice the pivotal role of the $e^{IPoM}_{t|T}$ regressor, constructed from the π^{IPoM}_{T} forecast, ultimately assigning a crucial role to the Central Bank in shaping public expectations; similar to the findings of Pedersen (2015).

Modelling strategy for time series models The modelling strategy is based on three building blocks: (i) utilisation of time-series components, (ii) variables related to the BCCh forecasts, and (iii) inclusion of exogenous indices such as IEC, EPU, and GPR terms. A tailored model selection process ensures that at least one variable from each block is included, following the hierarchical sequence: first (i), then (ii), and (iii) if there is sufficient room after incorporating (i) and (ii) according to the statistical significance of its individual regressors. The baseline specification is, therefore:

$$\begin{aligned} \pi^*_t \;=\; & \pi_0 + \phi_1 \pi^*_{t-1} + \phi_2 \pi^*_{t-2} + \rho \varepsilon_{t-1} + \\ & \beta_1 \pi^{IPoM}_{T} + \beta_2 \pi^{IPoM}_{T+1} + \gamma_1 e^{EEE}_{t|t+11} + \gamma_2 e^{EEE}_{t|t+23} + \gamma_3 e^{IPoM}_{t|T} + \gamma_4 e^{IPoM}_{t|T+1} + \gamma_5 e^{Target}_{t} + \\ & \alpha_1 Index_{t-1} + \alpha_2 Index_{t-2} + \alpha_3 Index_{t-3} + \alpha_4 Index_{t-4} + \alpha_5 Index_{t-j} \cdot \pi_t \\ & + \varepsilon_t, \end{aligned} \tag{6}$$

where $\{\pi_0, \varepsilon_t\}$ represent a constant and an error term, $\{\phi_1, \phi_2, \rho\}$ denote the time-series parameters, $\{\beta_1, \beta_2, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5\}$ correspond to the coefficients of BCCh forecasts, and $\{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5\}$ are the parameters associated with exogenous indices (*i.e.*, $Index_t = \{IEC_t, EPU_t, GPR_t\}$), including an interaction with current inflation at lag j, *i.e.*, $Index_{t-j} \cdot \pi_t$, with $j = \{1, 4, 6\}$. This is done in order to interpret the effect of the Index on expectations conditional on the current level of inflation. No statistical adjustments are applied to the IEC, EPU, and GPR series. Model selection involves setting certain parameters to zero in specific specifications to accommodate the error term, followed by an analysis of individual statistical significance.

The results of this dynamic exercise are presented in Table 1, providing robust evidence of the persistence of steady-state inflation expectations. The autoregressive coefficient of π^*_{t-1} consistently approaches or exceeds unity across all specifications, ranging between 1.041 and 1.248, even when autocorrelation in errors is controlled using an AR(1) coefficient.[9] This reinforces the notion that long-term deviations from the target tend to be self-sustaining and require either sustained periods of lower inflation and/or consistently accurate inflation forecasts. Note that, although IPoM forecasts are not directly statistically significant, they influence long-term deviations through the $e^{IPoM}_{t|T}$ regressor, which ranges between 0.057 and 0.077.[10] The results further highlight the influence of error-based regressors, particularly $e^{EEE}_{t|t+11}$ and $e^{IPoM}_{t|T}$, which remain statistically significant across the estimated models. This suggests that the formation of inflation expectations is strongly driven by discrepancies with IPoM forecasts–as previously suggested by Pedersen (2015)–, indicating that expectation deviations are not purely random but rather structured responses to forecast inaccuracies. Notice that the coefficient associated with $e^{IPoM}_{t|T}$ is consistently larger than that of $e^{EEE}_{t|t+11}$, with 0.057 as the minimum of $e^{IPoM}_{t|T}$ and 0.039 as the maximum of $e^{EEE}_{t|t+11}$, suggesting that EEE respondents align more closely with IPoM forecasts than with actual inflation. Notably, when IPoM forecasts overestimate inflation, expectations appear to revert more predictably, suggesting that agents dynamically adjust their forecasts based on perceived forecast errors rather than solely relying on the Central Bank's guidance.

[9] Note that in an AR(p)-X model, this does not pertain to unit root testing, as X variables and their volatility also play a role (Fuhrer, 2011).
[10] According to the estimates in columns (1) and (2), which exclude exogenous indexes, regressors such as π^{IPoM}_{T}, π^{IPoM}_{T+1}, and $e^{EEE}_{t|t+23}$, as well as e^{Target}_{t}, are not statistically significant and are therefore excluded from further analyses.

Table 1. Time-series models for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable: π_t^*											
π_{t-1}^*	1.128***	1.248***	1.079***	1.074***	1.091***	1.079***	1.080***	1.099***	1.041***	1.055***	1.061***
	(0.174)	(0.118)	(0.054)	(0.055)	(0.051)	(0.049)	(0.047)	(0.045)	(0.044)	(0.044)	(0.044)
π_{t-2}^*	-0.388***	-0.347***	-	-	-	-	-	-	-	-	-
	(0.089)	(0.094)	-	-	-	-	-	-	-	-	-
π_T^{IPoM}	0.219	0.108	-	-	-	-	-	-	-	-	-
	(0.202)	(0.100)	-	-	-	-	-	-	-	-	-
π_{T+1}^{IPoM}	0.153	-	-	-	-	-	-	-	-	-	-
	(0.148)	-	-	-	-	-	-	-	-	-	-
$e_{t\|t+11}^{EEE}$	0.025*	0.018	0.038***	0.038***	0.039***	0.036***	0.034***	0.033***	0.033***	0.032***	0.031***
	(0.013)	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
$e_{t\|t+23}^{EEE}$	-0.007	-	-	-	-	-	-	-	-	-	-
	(0.007)	-	-	-	-	-	-	-	-	-	-
$e_{t\|T}^{IPoM}$	0.310	0.165	0.075***	0.077***	0.072***	0.064***	0.070***	0.073***	0.057**	0.063***	0.062***
	(0.201)	(0.109)	(0.025)	(0.025)	(0.024)	(0.023)	(0.022)	(0.021)	(0.023)	(0.023)	(0.023)
e_t^{Target}	0.007	-	-	-	-	-	-	-	-	-	-
	(0.025)	-	-	-	-	-	-	-	-	-	-
$IEC_{t-j,j=\{1,2,3\}}$		-	0.048	0.040	0.080**	-	-	-	-	-	-
	-	-	(0.045)	(0.050)	(0.040)	-	-	-	-	-	-
$IEC_{t-1} \cdot \pi_t$	-	-	-0.011*	-0.010	-0.014**	-	-	-	-	-	-
	-	-	(0.006)	(0.007)	(0.006)	-	-	-	-	-	-
$EPU_{t-j,j=\{1,2,3\}}$		-	-	-	-	0.052	0.070	0.119***	-	-	-
	-	-	-	-	-	(0.044)	(0.043)	(0.038)	-	-	-
$EPU_{t-1} \cdot \pi_t$	-	-	-	-	-	-0.012**	-0.013**	-0.015***	-	-	-
	-	-	-	-	-	(0.006)	(0.005)	(0.004)	-	-	-
$GPR_{t-j,j=\{1,2,3\}}$		-	-	-	-	-	-	-	0.073	0.013	-0.036
	-	-	-	-	-	-	-	-	(0.055)	(0.048)	(0.038)
$GPR_{t-6} \cdot \pi_t$	-	-	-	-	-	-	-	-	-0.013**	-0.013**	-0.012**
	-	-	-	-	-	-	-	-	(0.006)	(0.006)	(0.006)
$Constant$	-1.107	-0.322	-0.007	0.004	-0.034	-0.005	-0.018	-0.069	-0.026	0.035	0.086*
	(0.703)	(0.304)	(0.053)	(0.054)	(0.048)	(0.047)	(0.045)	(0.043)	(0.063)	(0.057)	(0.050)
No. obs.	68	82	66	66	66	82	82	82	82	82	82
Adj. R-sq.	0.935	0.928	0.958	0.957	0.959	0.956	0.956	0.960	0.953	0.951	0.952
AR terms	No	No	1	1	1	1	1	1	1	1	1
Est. method	OLS/NW	OLS/NW	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "OLS/NW" = Ordinary Least Squares with Newey-West corrected standard deviations. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12.
Source: Author's elaboration.

When analysing the role of uncertainty and geopolitical tensions, a common finding emerges: deviations from the target tend to widen. However, when these indices interact with inflation, long-term deviations from the target tend to narrow.[11] Following this rationale, both IEC and EPU yield statistically significant results at the

[11] To further examine uncertainty and geopolitical shocks, Annex B presents VAR-based evidence on inflation's muted response.

third lag. This suggests that the inflation level itself plays a crucial role in shaping inflation expectations by catalyzing the influence of uncertainty. Beyond the confidence on IPoM forecasts, broader economic uncertainty has a direct impact on the formation of expectations. These findings reinforce the view that while monetary authorities can influence inflation expectations, the extent to which they remain anchored is also dependent on external macroeconomic conditions and agents' forward-looking behaviour.

Modelling strategy for simple switching models A second set of results beyond the policy horizon is based on simple switching regressions, following Hamilton (1994). This approach employs nonlinear modelling, assuming relationships that are subject to unobserved regime changes. Specifically, based on previous results, the dependent variable π_t^* follows a process that depends on the value of an unobserved discrete state variable s_t. In this analysis, two regimes are assumed ($M = 2$): a first regime ($m = 1$), characterised by lower uncertainty and abridged geopolitical tensions, dictated by lower values of a nonlinear transformation of exogenous index series, and a second regime ($m = 2$), reflecting higher uncertainty and heightened geopolitical tensions. The switching model assumes a distinct regression model for each regime, with some regressors varying by regime (π_{t-1}^*, $Index_i$, $Index_j \cdot \pi_t$, for selected i and j, and a AR(1) term), while others remain common across regimes ($e_{t|t+11}^{EEE}$). The conditional mean of π_t^* in regime m is given by:

$$\boldsymbol{\mu}_t(m) = \mathbf{X}_t' \boldsymbol{\beta}(m) + \mathbf{Z}_t' \gamma, \tag{7}$$

with $\mathbf{X}_t' = [\pi_{t-1}^*, Index_i, Index_j \cdot \pi_t]'$ and $\mathbf{Z}_t = [e_{t|t+11}^{EEE}]$. In this specification, $\boldsymbol{\beta}(m)$ and $\boldsymbol{\gamma}$ are vectors of coefficients, with $\boldsymbol{\beta}(m)$ indexed by regime for $\mathbf{X}_t$, while $\boldsymbol{\gamma}$ remains invariant across regimes. The errors are assumed to be normally distributed. The standard deviation $\boldsymbol{\sigma}$ may be regime dependent, denoted as $\boldsymbol{\sigma}(m) = \sigma_m$. Thus, the specification is formulated as:

$$\pi_t^* = \boldsymbol{\mu}_t(m) + \boldsymbol{\sigma}(m)(1 - \boldsymbol{\varphi}(m)L)\varepsilon_t, \tag{8}$$

when $s_t = m$, and where ε_t follows a standard normal distribution. This specification, which include a term to control for serial correlation, is referred to as *Simple Switching with Autocorrelation* (SSAR); see Hamilton (1989), and Frühwirth-Schnatter (2006), for details.

Regime probabilities are modelled with a Logit specification using the exogenous factors, specifically $\mathbf{G}_t = \{IEC_t, EPU_t, GPR_t\}$, and applying a nonlinear transformation following the rule:

$$Index_{\{0,1\}} = \begin{cases} 0 & \text{if } Index_t < Index_{t-1} + 3 \cdot \sigma^2_{Index_{t-1}} \\ 1 & \text{if } Index_t \geq Index_{t-1} + 3 \cdot \sigma^2_{Index_{t-1}}. \end{cases} \tag{9}$$

The coefficients δ are estimated using $\mathbf{G}_{t-1}^{\{0,1\}}$ conditional on the information set $\mathbf{I}_{t-1}$:

$$\mathbb{P}\left(s_t = m | \mathbf{I}_{t-1}, \delta\right) \equiv p_m(\mathbf{G}_{t-1}^{\{0,1\}}, \delta) = \frac{\exp\left(\mathbf{G}_{t-1}^{\{0,1\}\prime} \delta_m\right)}{\sum_{j=1}^{M} \exp\left(\mathbf{G}_{t-1}^{\{0,1\}\prime} \delta_j\right)}, \tag{10}$$

with $\delta = [\delta_1, \delta_2]$, using the identifying normalisation $\delta_2 = 0$. The presence of lagged variables implies lagged states, complicating the dynamics and requiring the treatment of a $p+1$-dimensional state variable representing both current and lagged states. The estimation approach treats switching probabilities as a *Restricted Markov Switching Model*, where transition probabilities do not depend on the origin regime:

$$\mathbb{P}\left(s_t = j | s_{t-1} = i\right) = p_{ij}(t) = p_j(t). \tag{11}$$

Thus, the specification to be estimated across M-regimes with transition probabilities depending on $\mathbf{G}_{t-1}^{\{0,1\}}$ is:

$$\pi_t^* = \overline{\pi}(m) + \boldsymbol{\phi}(m)\pi_{t-1}^* + \boldsymbol{\alpha}_1(m) Index_i + \boldsymbol{\alpha}_2(m) Index_j \cdot \pi_t + \gamma e_{t|t+11}^{EEE} + \boldsymbol{\sigma}(m)(1 - \boldsymbol{\varphi}(m)L)\varepsilon_t, \tag{12}$$

where $\{\overline{\pi}, \boldsymbol{\phi}, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \boldsymbol{\sigma}, \boldsymbol{\varphi}\}$ are regime-dependent vectors of coefficients, γ is a regime-invariant coeffecient, and ε_t is an error term.

Results appear in Table 2. Statistical significance depends on correct regime identification via Logit estimates in the "Probabilities parameters" panel. Negative significant coefficients are economically meaningful, especially when IEC identifies the high-uncertainty regime (columns (3), (6), (9)). In these cases, the lagged dependent variable and EEE forecast errors significantly shape expectations. Exogenous uncertainty has limited impact in Regime 1 but is stronger in Regime 2, where EPU reaches a significant coefficient of 0.444 (column (4)).

Table 2. Simple switching regression estimates for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: π_t^*									
Regime 1: Lower uncertainty, stablised geopolitical tensions									
Index:	IEC $\{i=t-3, j=t-1\}$			EPU $\{i=t-3, j=t-1\}$			GPR $\{i=t-3, j=t-6\}$		
π_{t-1}^*	1.448***	0.774***	1.064***	0.643***	0.287***	0.829***	1.302***	0.833***	0.826***
	(0.061)	(0.080)	(0.048)	(0.157)	(0.080)	(0.083)	(0.084)	(0.095)	(0.100)
$Index_i$	0.034	-0.025	0.035**	-0.030	-0.128**	-0.006	-0.650***	-0.034	-0.033
	(0.058)	(0.019)	(0.019)	(0.019)	(0.059)	(0.016)	(0.125)	(0.041)	(0.041)
$Index_j \cdot \pi_t$	-0.032***	0.004*	-0.017***	0.008**	0.015**	0.005**	-0.006	0.012	0.012
	(0.006)	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.018)	(0.008)	(0.008)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regime 2: Higher uncertainty, heightened geopolitical tensions									
π_{t-1}^*	0.715***	0.296***	0.699***	0.464***	0.751***	0.393***	0.753***	0.607***	0.599***
	(0.025)	(0.088)	(0.039)	(0.146)	(0.089)	(0.055)	(0.030)	(0.092)	(0.096)
$Index_i$	-0.026	-0.129*	-0.060**	0.444***	-0.023	-0.316***	0.029	-0.126	-0.127
	(0.022)	(0.077)	(0.026)	(0.106)	(0.019)	(0.057)	(0.044)	(0.118)	(0.117)
$Index_j \cdot \pi_t$	0.004	0.014*	-0.004	-0.019*	0.006**	0.024***	-0.007***	-0.002	-0.001
	(0.002)	(0.008)	(0.004)	(0.010)	(0.003)	(0.006)	(0.002)	(0.014)	(0.014)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common regressors									
$e_{t\|t+11}^{EEE}$	0.032***	0.029***	0.054***	0.019	0.029***	0.031***	0.035***	0.028***	0.027**
	(0.007)	(0.009)	(0.012)	(0.012)	(0.009)	(0.011)	(0.007)	(0.011)	(0.011)
Probabilities parameters (Logit estimates)									
$IEC_{\{0,1\}}$	1.167*	-0.438	-1.534***	0.174	0.262	-1.273**	0.835	-0.231	-0.979**
	(0.689)	(0.665)	(0.463)	(0.725)	(0.655)	(0.511)	(0.733)	(0.654)	(0.454)
$EPU_{\{0,1\}}$	0.595	-1.423**	-	-1.867***	1.437**	-	0.504	-1.260	-
	(0.684)	(0.645)	-	(0.717)	(0.630)	-	(0.881)	(0.644)	-
$GPR_{\{0,1\}}$	-0.243	-	-	-0.658	-	-	-0.130	-	-
	(0.677)	-	-	(0.609)	-	-	(0.900)	-	-
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	201	201	201	267	267	267	267	267	267
Std. dev. of regression	0.261	0.254	0.263	0.246	0.222	0.233	0.221	0.232	0.234
Log likelihood	107.6	97.30	96.74	101.7	99.38	96.76	101.0	97.47	94.97
Est. method	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Following the economic rationale of Table 1's results, there are some estimated negative coefficients associated with indices that may be explained by the fact that *the economy is already in a regime of heightened uncertainty and geopolitical tensions*. Moreover, the results indicate that, when comparing different regimes, the interaction of uncertainty measures with actual inflation reveals a pure de-anchoring effect: higher uncertainty significantly *increases* deviations from the target. Similar to the findings in Table 1, GPR does not play a major role either in expectation formation compared to the IEC and EPU indices or in the definition of regimes.

Overall, these switching regression results provide evidence of nonlinear dynamics in the formation of steady-state inflation expectations. The differential effects observed between the two regimes underscore the importance of considering regime-specific adjustments, which are further analysed using nonlinear binary-outcome models.

Modelling strategy for binary outcome models This subsection disregards the effects of persistence and memory in the series, allowing for an independent and non-linear analysis of deviations in the π_t^* series. To this end, a binary-outcome Probit model is estimated (Wooldridge, 2010). For this purpose, the latent variable $\pi^*_{\{0,1\}}$ is defined as dichotomous, taking the value of 1 when $\pi_t^* - 3\%$ is positive and 0 otherwise. Similarly to previous specifications, $\pi_t^* - 3\%$ depends on covariates, *i.e.*, $\pi_t^* - 3\% = \mathbf{x}_i'\boldsymbol{\beta} + \nu_i$, where $\mathbf{x}_i$ represents the covariates, $\boldsymbol{\beta}$ denotes the parameters to be estimated, and ν_i is an error term. Thus:

$$\pi_t^* - 3\% \Longrightarrow \pi^*_{\{0,1\}} = \begin{cases} 0 & \text{if } \pi_t^* - 3\% = \mathbf{x}_i'\boldsymbol{\beta} + \nu_i \leq 0 \\ 1 & \text{if } \pi_t^* - 3\% = \mathbf{x}_i'\boldsymbol{\beta} + \nu_i > 0. \end{cases} \tag{13}$$

Hence, the expected value of $\pi^*_{\{0,1\}}$ is:

$$\begin{aligned} \mathbb{E}\left[\pi^*_{\{0,1\}}\right] &= \mathbb{P}\left[\pi^*_{\{0,1\}} = 1|\mathbf{x}_i\right] \cdot (1) + \mathbb{P}\left[\pi^*_{\{0,1\}} = 0|\mathbf{x}_i\right] \cdot (0), \\ &= \mathbb{P}\left[\pi_t^* - 3\% > 0|\mathbf{x}_i\right], \\ &= \mathbb{P}\left[\mathbf{x}_i'\boldsymbol{\beta} + \nu_i > 0|\mathbf{x}_i\right], \\ &= \mathbb{P}\left[-\nu_i < \mathbf{x}_i'\boldsymbol{\beta}|\mathbf{x}_i\right], \\ &= F\left(\mathbf{x}_i'\boldsymbol{\beta}\right), \end{aligned} \tag{14}$$

where $F(\cdot)$ is the cumulative probability function of $-\nu_i$ which is assumed to be symmetric around zero. In the Probit specification, $F(\cdot)$ is assumed to follow the normal distribution, *i.e.*, $F\left(\mathbf{x}_i'\boldsymbol{\beta}\right) = \phi\left(\mathbf{x}_i'\boldsymbol{\beta}\right)$. From this, the marginal effect of $\mathbf{x}_i$ on $\pi^*_{\{0,1\}}$ corresponds to the nonlinear function $\partial\mathbb{P}\left[\pi^*_{\{0,1\}} = 1|\mathbf{x}_i\right]/\partial\mathbf{x}_i = \phi\left(\mathbf{x}_i'\boldsymbol{\beta}\right)\boldsymbol{\beta}$, where its standard deviations are computed using the Delta Method. The results of these estimations, using regressors similar to those in previous specifications, are presented in Table 3.

The findings indicate that the IPoM short-term inflation forecast (π_T^{IPoM}) has a strong and statistically significant impact on the probability of deviations in inflation expectations, with consistently positive coefficients across specifications, ranging between 0.983 and 2.136. Similarly, the distance to the target (e^{Target}) is also robustly significant, reaching a maximum of 2.136, displaying a negative coefficient throughout all specifications, ranging between -0.323 to -0.065. This suggests that respondents update their expectations based on Central Bank forecasts, though with varying magnitudes depending on the model, while always taking into account the distance to the actual inflation level. As a result, the probability of deviation decreases when actual inflation increases.

The IPoM forecast for December of the following year (π_{T+1}^{IPoM}) exhibits mixed significance, but when statistically significant, its influence is often greater than that of π_T^{IPoM} in some specifications; a signal towards anchoring since π_{T+1}^{IPoM} is already close to the target. These two measures also serve as indicators of the overall inflation level to some extent. When analysing series in differences of levels, 11-month ahead forecast errors (e_{t+11}^{EEE}) display positive and significant coefficients, reaching a maximum marginal effect of 0.057, as does the difference between EEE and IPoM forecasts (e_T^{IPoM}). This suggests that agents adjust their expectations based on past inaccuracies, while also being more responsive to IPoM forecasts than to their own past forecast errors, further highlighting the Central Bank's influence on expectation formation.

Table 3. Probit marginal effects estimates for $\pi^*_{\{0,1\}}$ (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent variable: $\pi^*_{\{0,1\}}$														
π_T^{IPoM}	1.167***	0.983***	2.093***	2.136***	0.738***	1.187***	1.384***	1.434***	0.852***	1.205***	1.341***	1.319***	0.988***	1.558***
	(0.176)	(0.135)	(0.550)	(0.868)	(0.128)	(0.162)	(0.239)	(0.236)	(0.174)	(0.158)	(0.221)	(0.219)	(0.170)	(0.215)
π_{T+1}^{IPoM}	0.127	-	1.011***	0.991	0.868***	-	0.293	0.263	0.400	-	0.309**	0.306	0.482*	-
	(0.244)	-	(0.452)	(0.645)	(0.386)	-	(0.276)	(0.275)	(0.306)	-	(0.257)	(0.251)	(0.281)	-
e_{t+11}^{EEE}	0.038**	0.024	0.052**	0.052*	0.028***	0.024	0.043***	0.040**	0.030***	0.023	0.042***	0.041***	0.057**	0.035*
	(0.017)	(0.016)	(0.022)	(0.030)	(0.012)	(0.016)	(0.015)	(0.016)	(0.016)	(0.017)	(0.015)	(0.015)	(0.023)	(0.017)
e_{t+23}^{EEE}	-0.014	-	0.007	-0.002	-	-	-0.024*	-0.024	-	-	-0.030**	-0.031**	-	-
	(0.015)	-	(0.020)	(0.021)	-	-	(0.014)	(0.015)	-	-	(0.013)	(0.013)	-	-
e_T^{IPoM}	1.098***	0.922***	1.915***	1.952**	0.728***	1.156***	1.306***	1.376***	0.822***	1.243***	1.241***	1.223***	0.930***	1.522***
	(0.200)	(0.184)	(0.494)	(0.790)	(0.150)	(0.214)	(0.260)	(0.257)	(0.226)	(0.211)	(0.229)	(0.230)	(0.197)	(0.253)
e^{Target}	-0.094**	-0.129***	-0.169***	-0.232***	-0.092***	-0.183***	-0.125***	-0.141***	-0.113***	-0.190***	-0.124***	-0.065***	-0.102***	-0.323***
	(0.038)	(0.035)	(0.036)	(0.076)	(0.028)	(0.045)	(0.040)	(0.044)	(0.035)	(0.039)	(0.037)	(0.046)	(0.035)	(0.060)
$IEC_{\{0,1\}}$	-	-	0.197***	-	0.128	-0.146	-	-	-	-	-	-	-	-
	-	-	(0.035)	-	(0.086)	(0.193)	-	-	-	-	-	-	-	-
$IEC_{\{0,1\}} \cdot \pi_t$	-	-	-	0.057***	-	0.083	-	-	-	-	-	-	-	-
	-	-	-	(0.018)	-	(0.056)	-	-	-	-	-	-	-	-
$EPU_{\{0,1\}}$	-	-	-	-	-	-	0.059	-	0.110	-0.272	-	-	-	-
	-	-	-	-	-	-	(0.093)	-	(0.115)	(0.223)	-	-	-	-
$EPU_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	0.028	-	0.134**	-	-	-	-
	-	-	-	-	-	-	-	(0.024)	-	(0.059)	-	-	-	-
$GPR_{\{0,1\}}$	-	-	-	-	-	-	-	-	-	-	-0.136***	-	0.419***	-0.534***
	-	-	-	-	-	-	-	-	-	-	(0.074)	-	(0.181)	(0.189)
$GPR_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	-	-	-	-	0.057***	-	0.190***
	-	-	-	-	-	-	-	-	-	-	-	(0.028)	-	(0.050)
No. obs.	69	83	53	53	57	67	62	62	66	76	62	62	66	76
Pseudo R-sq.	0.5872	0.4315	0.8654	0.8506	0.5786	0.5066	0.7000	0.7075	0.4914	0.5084	0.7001	0.7020	0.5477	0.5505
Est. method	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML

(†) Delta-method-based standard deviation in parentheses. "ML" = Maximum likelihood estimation method. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Beyond BCCh forecasts, uncertainty measures significantly impact deviations from the inflation target. The inclusion of the IEC, EPU, and GPR reveals that heightened uncertainty contributes to the unanchoring of inflation expectations. In particular, interactions between uncertainty indicators and actual inflation (particularly $GPR_{\{0,1\}} \cdot \pi_t$; columns (11) to (14)) show statistically significant effects, confirming that greater uncertainty amplifies deviations from the target, whereas lower uncertainty conditions help keep expectations more firmly anchored.

For the purpose of this analysis, the statistical significance of external indices in the steady state still indicates expectations anchoring, albeit with a degree of shared influence, limiting the Central Bank's ability to fully steer inflation expectations towards the target. As this evidence is based on non-linear models, the influence of BCCh forecasts on experts' expectations depends, at the very least, on the prevailing level of exogenous uncertainty in the economy.

4 Robustness results

4.1 Integrating measures of uncertainty and geopolitical tensions

Previous evidence suggests a role for exogenous indices both in determining steady-state deviations in inflation expectations and in distinguishing between regimes of low versus high uncertainty and geopolitical tensions. However, the results remain somewhat specific to the regression specification and are sensitive to the lag with which heightened uncertainty and geopolitical tensions are reflected in responses to the EEE survey. To address this issue, I employ the first principal component of the three indices as a composite measure capturing major exogenous macroeconomic disturbances. This principal component, labelled as "*Uncertainty*", is included as a standard regressor in both types of time-series regressions, while it is transformed into a binary variable to define the regimes in simple switching regressions. The binary variable "$Uncertainty_{\{0,1\}}$", used to identify regression regimes, is constructed as follows:

$$Uncertainty_{\{0,1\}} = \begin{cases} 1 & \text{if } Uncertainty_t > \overline{Uncertainty}_t \\ 0 & \text{if } Uncertainty_t \leq \overline{Uncertainty}_t, \end{cases} \tag{15}$$

where $\overline{Uncertainty}_t$ is the sample mean of $Uncertainty_t$ up to period t. This binary regressor, both contemporaneous ($Uncertainty_{\{0,1\},t}$) and lagged by four months ($Uncertainty_{\{0,1\},t-4}$), is subsequently used in binary-outcome regressions.

The results presented in Tables 4, 5, and 6 evaluate the robustness of the uncertainty component in determining long-term inflation expectations. Table 4 confirms that expectations exhibit strong persistence, with autoregressive terms remaining statistically significant across all models and only in one case exceeding unity. The Central Bank's short-term inflation forecast (π_T^{IPoM}) has an influence, but its impact diminishes in specifications that incorporate uncertainty measures lagged by three and four months. Short-term forecast errors ($e_{t|t+11}^{EEE}$) and deviations from IPoM forecasts (e_T^{IPoM}) remain significant, although their magnitudes vary across specifications. The interaction term ($Uncertainty_{t-1} \cdot \pi_t$) is statistically significant across specifications, with coefficients ranging from -0.019 to -0.012, consistently negative, as observed when using the uncertainty indices individually. Interestingly, the standalone uncertainty regressor indicates that EEE respondents require four months to fully reflect this information in their answers, with this lag also yielding the highest coefficient among those considered.

The switching regression estimates in Table 5 reveal that uncertainty influences inflation expectations differently across regimes. Under low uncertainty, expectations are more stable, and uncertainty does not play a major role in determining deviations, as indicated by reduced coefficients and lower statistical significance. In contrast, during high-uncertainty periods, both the uncertainty index itself and its interaction with inflation exhibit consistent statistical significance with stable coefficients. Notably, the uncertainty index also plays a role in defining the regimes through Logit estimates. The results in columns (1) and (5) confirm this evidence, displaying the expected sign, which allows for interpreting a high score as indicative of heightened uncertainty and elevated geopolitical tensions. However, when using the uncertainty component as a regressor, neither EPU nor GPR alone is sufficient to distinguish between regimes.

Table 4. Time-series models for π_t^* with "*Uncertainty*" measure (†)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: π_t^*						
π_{t-1}^*	0.580**	0.844**	0.861**	0.901**	0.920**	1.068***
	(0.126)	(0.094)	(0.098)	(0.105)	(0.102)	(0.041)
π_T^{IPoM}	0.532**	0.229**	0.207*	0.166	0.144	-
	(0.144)	(0.084)	(0.086)	(0.093)	(0.091)	-
π_{T+1}^{IPoM}	0.025	-	-	-	-	-
	(0.082)	-	-	-	-	-
$e_{t\|t+11}^{EEE}$	0.051**	0.046**	-	0.047**	-	0.037***
	(0.009)	(0.009)	-	(0.009)	-	(0.008)
$e_{t\|t+23}^{EEE}$	-0.007	-	-	-	-	-
	(0.008)	-	-	-	-	-
$e_{t\|T}^{IPoM}$	0.650**	0.330**	0.046**	0.264*	-	-
	(0.146)	(0.095)	(0.009)	(0.103)	-	-
e_t^{Target}	-0.039	-	-	-	-	-
	(0.023)	-	-	-	-	-
$Uncertainty_{t-1} \cdot \pi_t$	-0.019**	-0.016**	-0.014**	-0.013**	-0.013**	-0.012***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003	(0.003)
$Uncertainty_{t-1}$	0.080*	0.047	-	-	-	-
	(0.033)	(0.025)	-	-	-	-
$Uncertainty_{t-2}$	-	-	0.037	-	-	-
	-	-	(0.027)	-	-	-
$Uncertainty_{t-3}$	-	-	-	0.037	-	-
	-	-	-	(0.024)	-	-
$Uncertainty_{t-4}$	-	-	-	-	0.044*	0.058***
	-	-	-	-	(0.021)	(0.019)
$Constant$	-1.649**	-0.679*	-0.610*	-0.490	-0.422	0.024
	(0.425)	(0.258)	(0.266)	(0.287)	(0.282)	(0.022)
No. obs.	78	82	82	82	82	82
Adj. R-sq.	0.967	0.961	0.960	0.958	0.960	0.958
AR terms	1	1	1	1	1	1
Est. method	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "OLS/NW" = Ordinary Least Squares with Newey-West corrected standard deviations. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Finally, the Probit model estimates in Table 6 support the main findings obtained using standalone exogenous indices, as well as those from Table 5, confirming that rising uncertainty increases the probability of expectation deviations and that the most significant impact of uncertainty on EEE responses occurs with a four-month lag; a marginal effect of 0.474 (column (5)). The sign of the uncertainty component aligns with the baseline specifications in Table 4, being positive for the unconditional level and negative for the interaction term. In the specifications presented in columns (4) and (5), the marginal effect of uncertainty is greater than in all previous similar specifications, though it remains below that of π_T^{IPoM} and e_T^{IPoM}. Overall, these findings reinforce the notion that heightened uncertainty reduces the Central Bank's ability to fully steer inflation expectations towards the target, yet it still retains an influence on steady-state expectations.

Table 5. Simple switching regression estimates for π_t^* with "*Uncertainty*" measure (†)

	(1)	(2)	(3)	(4)	(5)
Dependent variable: π_t^*					
Regime 1: Lower uncertainty, stablised geopolitical tensions					
π_{t-1}^*	0.718***	1.327***	0.732***	0.784***	0.718***
	(0.035)	(0.040)	(0.034)	(0.032)	(0.034)
$Uncertainty_{t-4}$	0.004	0.062**	0.006	-0.004	0.004
	(0.009)	(0.024)	(0.010)	(0.006)	(0.010)
$Uncertainty_{t-1} \cdot \pi_t$	0.001	-0.022***	0.0004	0.003*	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
AR terms	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes
Regime 2: Higher uncertainty, heightened geopolitical tensions with "*Uncertainty*" measure					
π_{t-1}^*	0.927***	0.700***	0.920***	0.847***	0.926***
	(0.067)	(0.022)	(0.070)	(0.076)	(0.066)
$Uncertainty_{t-4}$	0.099***	-0.010	0.100***	0.123**	0.100***
	(0.036)	(0.014)	(0.037)	(0.050)	(0.036)
$Uncertainty_{t-1} \cdot \pi_t$	-0.012**	0.001**	-0.013**	-0.017***	-0.012**
	(0.005)	(0.002)	(0.005)	(0.006)	(0.005)
AR terms	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes
Common regressors					
$e_{t\|t+11}^{EEE}$	0.027***	0.033***	0.028***	0.024***	0.027***
	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)
Probabilities parameters (Multinomial Logit estimates)					
$Uncertainty_{\{0,1\}}$	-0.810**	-	-	-	-0.787*
	(0.413)	-	-	-	(0.413)
$IEC_{\{0,1\}}$	-	1.343**	-0.453	-1.120***	-
	-	(0.643)	(0.551)	(0.431)	-
$EPU_{\{0,1\}}$	-	0.510	-0.680	-	-
	-	(0.631)	(0.556)	-	-
$GPR_{\{0,1\}}$	-	-0.245	-	-	-0.203
	-	(0.591)	-	-	(0.531)
Constant	Yes	Yes	Yes	Yes	Yes
No. obs.	240	204	204	204	240
Std. dev. of regression	0.230	0.224	0.226	0.231	0.230
Log likelihood	138.5	117.8	105.4	98.81	138.6
Est. method	BHHH	BHHH	BHHH	BHHH	BHHH

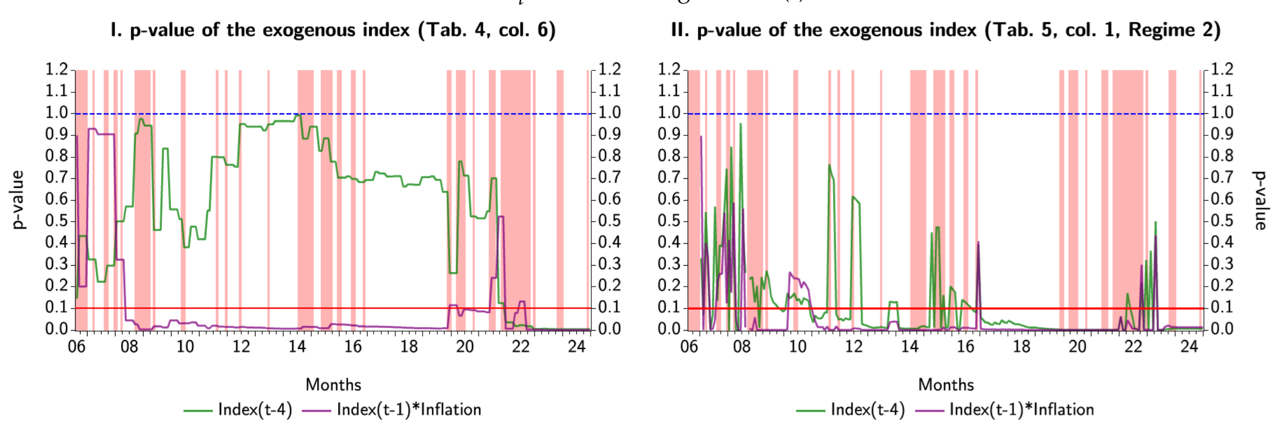
(†) Standard deviation in parentheses. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Table 6. Probit marginal effects estimates for $\pi^*_{\{0,1\}}$ with "*Uncertainty*" measure (†)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: $\pi^*_{\{0,1\}}$						
π_T^{IPoM}	1.506***	1.627***	1.200***	1.871***	1.801***	1.165***
	(0.233)	(0.264)	(0.174)	(0.343)	(0.313)	(0.182)
π_{T+1}^{IPoM}	0.370	-	-	0.462	-	-
	(0.249)	-	-	(0.282)	-	-
e_{t+11}^{EEE}	0.044***	0.044***	0.035*	0.038**	0.033*	0.033*
	(0.015)	(0.015)	(0.018)	(0.017)	(0.017)	(0.018)
e_{t+23}^{EEE}	-0.026**	-0.026**	-	-0.035**	-0.031*	-
	(0.012)	(0.013)	-	(0.016)	(0.018)	-
e_T^{IPoM}	1.426***	1.556***	1.174***	1.813***	1.764***	1.129***
	(0.256)	(0.297)	(0.229)	(0.359)	(0.360)	(0.239)
e^{Target}	-0.131***	-0.129***	-0.189***	-0.110***	-0.085***	-0.178***
	(0.040)	(0.039)	(0.044)	(0.041)	(0.033)	(0.041)
$Uncertainty_{\{0,1\},t}$	0.099	0.118	-0.122	-	-	-
	(0.079)	(0.082)	(0.186)	-	-	-
$Uncertainty_{\{0,1\},t} \cdot \pi_t$	-	-	0.081	-	-	0.046*
	-	-	(0.052)	-	-	(0.026)
$Uncertainty_{\{0,1\},t-4}$	-	-0.029	-	0.442***	0.474***	0.051
	-	(0.022)	-	(0.153)	(0.158)	(0.086)
$Uncertainty_{\{0,1\},t-4} \cdot \pi_t$	-0.019	-	-	-0.132***	-0.151***	-
	(0.018)	-	-	(0.046)	(0.050)	-
No. obs.	71	71	76	71	71	75
Pseudo R-sq.	0.7090	0.6914	0.4873	0.7467	0.7213	0.4797
Est. method	ML	ML	ML	ML	ML	ML

(†) Delta-method-based standard deviation in parentheses. "ML" = Maximum likelihood estimation method. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Figure 8. Recursive estimate of the p-value for the exogenous index in π_t^* time-series regressions (*)



(*) Panel I depicts the Ordinary Least Squares recursive estimates of the p-value for the parameters associated with $Uncertainty_{t-4}$ and $Uncertainty_{t-1} \cdot \pi_t$ from the specification in column (6) of Table 4. Panel II presents the recursive estimates of the p-value for the parameters $Uncertainty_{t-4}$ and $Uncertainty_{t-1} \cdot \pi_t$ from the specification in column (1) of Table 5. Shaded bars: $Uncertainty_t = 0$. Initial estimation sample: 2001.9–2006.8 (60 observations; monthly estimates). Last estimation sample: 2001.9–2024.12 (280 observations). Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

4.2 Assessing the evolving role of uncertainty

It is important to note that the evidence presented is primarily based on regression estimates using the full available sample. This approach may be dependent on the model selection strategy described earlier and the specific results derived from it. To overcome this limitation, two specifications are selected, and the statistical significance of the uncertainty component is examined over time using recursive estimates. The chosen specification for the linear time-series models corresponds to column (6) of Table 4, while for the non-linear models, it corresponds to column (1) of Table 5, specifically within the high-uncertainty regime.

Figure 8 presents recursive estimates of the p-value for the exogenous indices associated with the two regressors containing information on the uncertainty components. Naturally, a declining p-value trajectory suggests increasing statistical relevance of the exogenous index in explaining deviations in π_t^*.

The results in Figure 8, panel I, reveal that, interestingly, in the linear regressions, both regressors become statistically significant only from 2021.11 onwards and remain so until the end of the sample. This represents a unique hysteresis phenomenon caused by the impact of the COVID-19 pandemic on inflation expectations. Conversely, panel II suggests that while this is not the first instance in which both regressors are significant, they only exhibit statistical significance during the final period of the sample when uncertainty is high. Notably, this does not occur during the 2008-09 *Global Financial Crisis* but instead take place when realised inflation averaged 3.42% (between 2016.11 and 2022.5).

These results reveal the unprecedented nature of expectation formation, which, unlike in previous episodes, accounts for deviations from the target by incorporating uncertainty and inflationary shocks that persist beyond the time frame in which EEE respondents provide their survey answers.

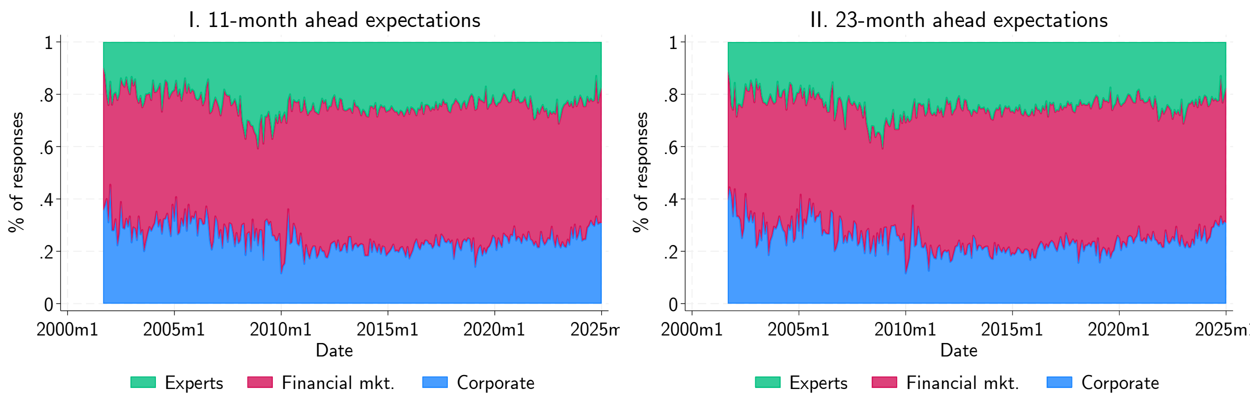
4.3 Composition of EEE respondents

To further analyse the composition of EEE responses, this subsection delves into the microdata at the individual level, replicating the empirical analysis used with aggregate expectations. By examining respondent-level heterogeneity, the analysis seeks to uncover systematic differences in expectation formation across: (i) expert forecasters, (ii) financial market participants, and (iii) corporate sector respondents. This approach allows for a deeper understanding of how individual responses contribute to observed patterns in inflation expectations and their deviations from the target.

4.3.1 Sensitivity of experts, financial market participants, and corporate participants to actual inflation

Figure 9 presents the time-varying composition of survey respondents by category for inflation expectations at 11 months ahead (panel I) and 23 months ahead (panel II). The proportions of each group remain relatively stable over the whole sample, with experts and financial-market participants consistently accounting for the majority of responses. There are mild fluctuations–for instance, a slight increase in the share of financial-market respondents in the later sample–but no abrupt changes that would indicate a sample selection shift. This stability in respondent mix ensures that subsequent results on expectation anchoring are not driven by changing survey demographics. In other words, any regime-dependent changes in expectations can be attributed to agents' behaviour under differing economic conditions, rather than to a compositional artefact.

Figure 9. Composition of EEE responses to selected inflation expectation questions over time (*)

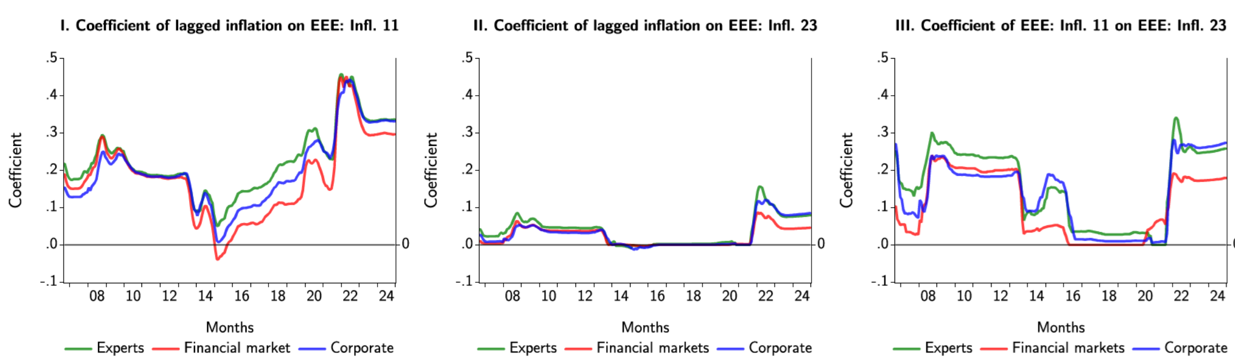


(*) Sample: 2001.9–2024.12 (280 observations). Source: Author's calculations based on data from the Central Bank of Chile.

Figure 10 replicates the OLS rolling-window estimates presented in Figure 1. The two coefficients related to the pass-through from actual to expected inflation exhibit notable time variation, reflecting evolving anchoring dynamics (see panels I and II). For h=11, throughout much of the early and mid-sample period, the coefficient on actual inflation remains stable, hovering around 0.20 percentage points (pp), which is consistent with well-anchored expectations. It is not until late 2019, and particularly during the post-pandemic period, that inflation surprises begin to have a substantial impact on expected inflation. This coefficient increases markedly, exceeding 0.40 pp in 2022 and failing to return to pre-pandemic levels. However, in the second half of the sample, responses from financial market participants are consistently lower than those from the corporate sector and, more significantly, lower than those from experts. This increase suggests that inflation shocks started to significantly influence short-run expectations, particularly among experts, signalling weaker anchoring in high-inflation episodes for these agents. Notably, a similar dynamic occurs for expectations at h=23, albeit at a different scale.

A comparable pattern is observed for the cross-horizon pass-through coefficient (see panel III). During stable periods, long-term expectations remain largely insulated from fluctuations in short-term expectations. However, in volatile regimes, the pass-through increases, surpassing 0.30 pp in 2022 and remaining steady thereafter, with only one exception. Notably, this coefficient, when estimated for financial market participants, reverts to levels observed in 2010–2014, and this adjustment occurs earlier for this group than for others. This suggests that, as inflation accelerated, deviations at the one-year horizon were more readily transmitted to two-year-ahead expectations, particularly among experts and academics.

Figure 10. Rolling-window coefficients of actual inflation on inflation expectations
and the pass-through between expectation horizons (*)



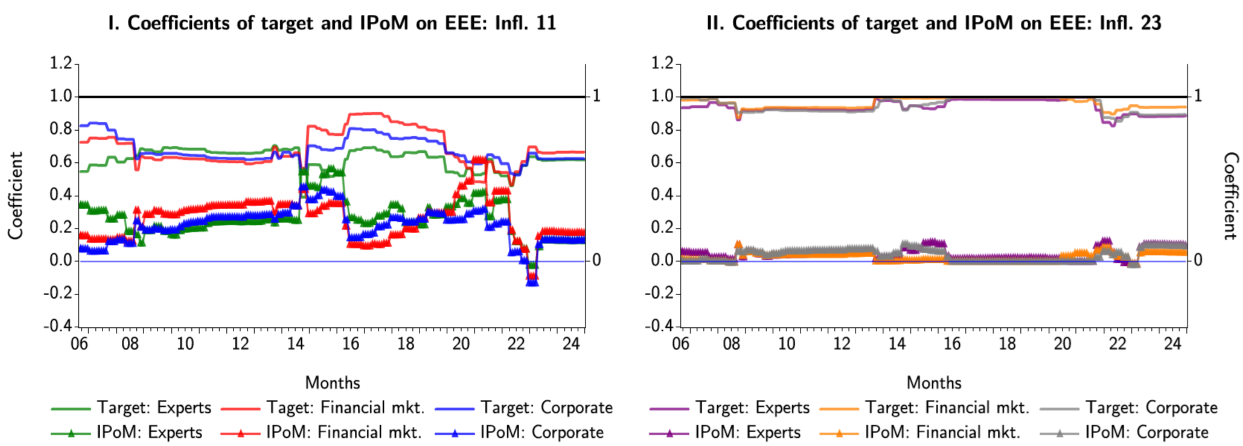
(*) See notes to Figure 1. Rolling-window size: 60 observations. Initial estimation sample: 2001.9–2006.8 (monthly estimates). Full sample: 2001.9–2024.12 (280 observations). Confidence intervals: ±2 standard deviations. Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

Figure 11 examines heterogeneity in anchoring by estimating equation (5) for different respondent groups and plotting the rolling-window coefficients on the inflation target (λ^{Target}) and the Central Bank's December forecast for the current year from the IPoM (λ^{IPoM}). Panel I reveals a clear pattern of cross-sectional differences. Financial market participants exhibit consistently high λ^{Target} coefficients—hovering around 0.70 pp and remaining relatively stable over time—indicating that their long-term expectations are firmly anchored to the official target. In contrast, experts and corporate respondents display lower average λ^{Target} values, with greater volatility. Notably, during periods of heightened inflation uncertainty (*e.g.* post-2021), λ^{Target} for experts and corporate respondents declines further, suggesting that these agents place less weight on the target, thereby allowing greater deviations in their expectations.

Conversely, panel II illustrates that experts and corporate respondents place slightly more reliance on the Central Bank's forecasts (higher λ^{IPoM}) than financial market participants. In contrast, financial participants exhibit a relatively muted response to IPoM forecasts remains modest), consistent with their expectation of inflation converging to the target.

Overall, this figure confirms heterogeneous anchoring behaviour, with financial market participants keeping expectations anchored to the target (high λ^{Target} and low λ^{IPoM}), while experts and corporate sector respondents are more inclined to incorporate current forecasts and deviate from the target under conditions of economic stress. This evidence aligns with earlier findings, indicating that confidence in the target persists overall but can erode for certain agents amid exogenous uncertainty.

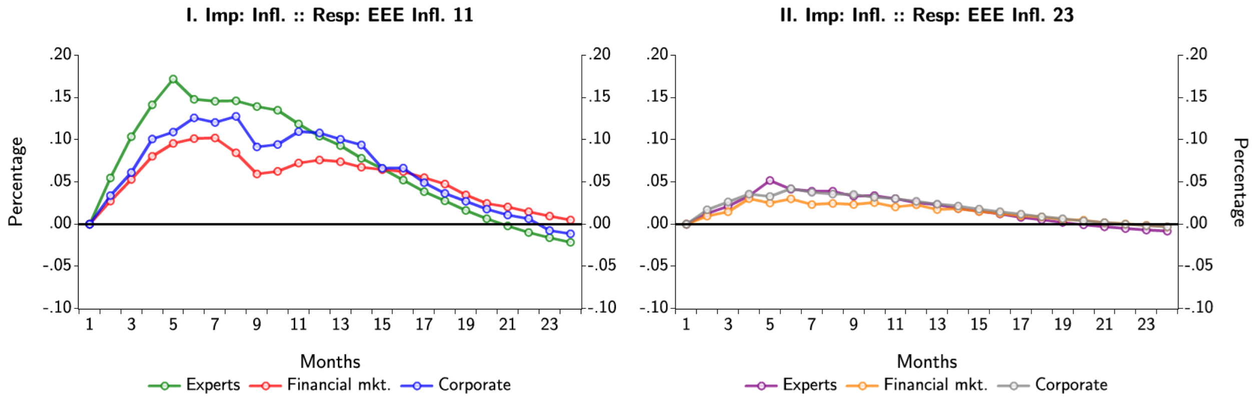
Figure 11: Rolling-window coefficients of inflation target and IPoM inflation forecasts on the inflation expectations of different agents (*)



(*) Panels I and II depict the Ordinary Least Squares rolling estimates of the λ^{Target} and λ^{IPoM} parameters from the regression of equation (5). Initial estimation sample: 2001.9–2006.8 (60 observations; monthly estimates). Parameter $\lambda^{\pi} = 1 - \lambda^{Target} - \lambda^{IPoM}$ not shown. Full sample: 2001.9–2024.12 (280 observations). Confidence intervals: ±2 standard deviations. Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

Figure 12 presents impulse response functions from the same VAR analysis as before, quantifying the effect of an exogenous inflation shock on 11- and 23-month-ahead inflation expectations across different respondent groups. The VAR is estimated using the full sample (2001.9–2024.12; 280 observations). The results show that all groups exhibit a persistent reaction, which dissipates approximately 20 months after the shock. The response of experts' expectations is noticeably stronger and more prolonged, peaking at 0.17 pp five periods after the shock. In contrast, for financial market respondents, the response remains moderate, consistently below 0.10 pp, reaffirming their anchored behaviour. The fact that the impulse response function for the financial sector is comparatively contained further confirms the anchoring role of the inflation-targeting regime in financial markets and a more reactive behaviour of experts.

Figure 12: Impulse response function estimates for a one-standard-deviation shock in actual inflation and response of expected inflation of different agents (*)



(*) Impulse response to Cholesky one-standard-deviation innovations (adjusted for degrees of freedom). The 95% confidence intervals are computed using Monte Carlo standard errors with 5000 replications. Full sample: 2001.9–2024.12 (280 observations). Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

4.3.2 Regression results for experts, financial market participants, and corporate participants

Regression estimates for the different types of agents are presented in the same manner as before (Table 1: Linear time-series models, Table 2: Simple switching regressions, and Table 3: Probit estimates), with results provided in Annex C for experts, Annex D for financial market participants, and Annex E for the corporate sector.

Table C1 presents the Ordinary Least Squares estimates for the determinants of steady-state expected inflation relative to the 3% target using experts' data. Persistence coefficients are always statistically significant and below unity, which is expected, as this group allows room for explanatory variables beyond the dependent variable itself. The coefficient on the 11-month-ahead forecast error is consistently positive and statistically significant, ranging between 0.015 and 0.024, confirming that experts account for their forecast errors when responding to the EEE. Meanwhile, the Central Bank's December forecast revisions (e_T^{IPoM}) exerts a positive and significant effect, with coefficients exceeding those of forecast errors, indicating that agents revise their expectations in response to BCCh forecasts. These estimates do not attribute a major role to exogenous factors related to uncertainty or geopolitical tensions, reaffirming the role of e_{t+11}^{EEE} and recent inflation developments in shaping experts' long-term expectations.

Table C2 extends and confirms previous conclusions regarding these agents by assigning a statistically significant role to persistence and a significant role solely to GPR in the heightened uncertainty regime, though without determining the regimes. The evidence for EPU and GPR appears episodic, as there is no consistent overlap in statistical significance between regime-specific regressors and regime determination. Additionally, EEE forecast errors at the 11-month-ahead horizon ($e_{t|t+11}^{EEE}$) are never statistically significant as a common regressor, exhibiting low values and suggesting that expectations are formed based on actual inflation levels rather than adjustments to previous forecasts.

In turn, Table C3 presents Probit marginal effects estimates for the probability of inflation expectations deviating from the target using experts' data. The Central Bank's inflation forecast (π_T^{IPoM}) remains a key determinant, exhibiting a positive and highly significant effect, achieving a maximum marginal effect of 1.550, confirming that experts adjust their expectations in response to BCCh forecasts. Similarly, the 11-month-ahead forecast error (e^{EEE}_{t+11}) is mostly positive but as before not statistically significant. The deviation of actual inflation from the target (e^{Target}) enters negatively and significantly, reinforcing the anchoring hypothesis, as expectations remain more stable when actual inflation is close to the target. The inclusion of IEC, EPU, and GPR reveals that heightened geopolitical tensions (*i.e.*, GPR) increase the probability of unanchoring, showing a marginal effect up to 0.368, with interaction terms indicating that inflation shocks exert a stronger impact in high-uncertainty environments. These findings underscore the critical role of Central Bank forecasts in expectation formation, while highlighting the importance of geopolitical stability in preserving anchored inflation expectations.

The time-series estimates for π^*_t using financial market participants' data are reported in Table D1, confirming strong persistence in inflation expectations across all specifications. The 11-month-ahead forecast error ($e^{EEE}_{t|t+11}$) is positive and statistically significant, indicating that agents adjust expectations based on past forecast errors, while the Central Bank's short-term forecast error (e^{IPoM}_{T}) remains largely non-significant, suggesting a limited role in shaping expectations. The introduction of uncertainty measures reveals that heightened uncertainty weakens anchoring, particularly for IEC and EPU, displaying a coefficient up to 0.072 for IEC and 0.068 for EPU. These results suggest that expectations remain persistent but become more sensitive to exogenous uncertainty shocks, highlighting the importance of closely monitoring geopolitical risks to maintain stable inflation expectations.

The simple switching regression estimates for steady-state inflation expectations inferred from financial market participants are presented in Table D2. The dependent variable exhibits significant persistence across both low- and high-uncertainty regimes, though with differing magnitudes. Under high uncertainty, persistence is lower than in the stabilised uncertainty regime, assigning a significant role to exogenous uncertainty indices. Interaction terms play a partial role, while the common regressor for the 11-month-ahead forecast error remains positive and significant, confirming that agents adjust based on past errors. The EPU significantly reduces the probability of remaining in a low-uncertainty regime, whereas GPR has no clear effect on regime determination. The model confirms that inflation expectations follow non-linear dynamics, displaying greater sensitivity to shocks in uncertain periods.

Table D3 presents Probit marginal effects estimates using financial market participants' data. The Central Bank's inflation forecast (π^{IPoM}_{T}) remains positive when statistically significant, confirming that agents consider BCCh forecasts when forming their expectations. Similarly, the next-year December forecast (π^{IPoM}_{T+1}) plays a mixed role, with varying significance across specifications. The 11-month-ahead forecast error (e^{EEE}_{t+11}) is mostly positive but not always significant, suggesting limited learning from past errors, in line with previous conclusions drawn from these agents' responses. The deviation from the target (e^{Target}) is negative and significant, reinforcing the anchoring hypothesis. Uncertainty indices, particularly GPR, significantly increase the probability of unanchoring, with interaction terms amplifying inflation shocks in high-uncertainty periods.

For their part, Table E1 presents time-series estimates for corporate sector participants' inflation expectations, confirming strong persistence across all specifications. The Central Bank's forecasts are non-significant, implying that corporate participants rely on alternative indicators rather than BCCh forecasts, a finding further supported by the non-significance of the $e^{IPoM}_{t|T}$ and $e^{IPoM}_{t|T+1}$ regressors. The 11-month-ahead forecast error ($e^{EEE}_{t|t+11}$) is positive and statistically significant, suggesting that firms adjust expectations based on past forecast errors, though its magnitude is smaller than in other respondent groups. The inclusion of exogenous uncertainty measures reveals no significant role for general uncertainty, but geopolitical tensions negatively affect anchoring. Interaction terms with GPR suggest that this effect is mitigated when actual inflation is already high. These results confirm that corporate inflation expectations are highly persistent, primarily influenced by their own past errors, with limited influence from other determinants, apart from GPR.

Simple switching regression estimates for corporate sector participants' inflation expectations are presented in Table E2. Expectations exhibit strong persistence across both regimes, though lower under high uncertainty. Exogenous indices display stronger and more significant effects in the high-uncertainty regime, suggesting that corporate expectations become more influenced by uncertainty during volatile periods. Interaction terms are mostly negative and significant, indicating that higher uncertainty dampens the effect of inflation shocks on expectations. The 11-month-ahead forecast error ($e^{EEE}_{t|t+11}$) remains positive and significant across all specifications, confirming that firms adjust expectations based on past errors. A notable feature of these estimates is that no single index systematically determines the transition to a heightened uncertainty regime. However, considering previous findings for this group, this result may serve as evidence of anchoring, as expectations appear to rely primarily on persistence and forecast errors rather than external indices.

Finally, Table E3 presents Probit marginal effects estimates for corporate sector participants' inflation expectations. The Central Bank's inflation forecast (π_T^{IPoM}) remains positive and highly significant, confirming that firms incorporate BCCh forecasts when forming expectations. The 11-month-ahead forecast error (e_{t+11}^{EEE}) is mostly positive but not always significant, indicating limited learning from past forecasting errors. The deviation from the target (e^{Target}) is negative and significant, reinforcing the anchoring hypothesis, as expectations remain more stable when inflation is near the target. Uncertainty measures, particularly GPR, significantly increase the probability of unanchoring, while interaction terms suggest that inflation shocks have an amplifying effect in high-uncertainty periods. Thus, corporate sector expectations remain anchored under normal conditions but become more sensitive to inflation and uncertainty shocks.

5 Concluding remarks

The stability of inflation expectations is crucial for effective monetary policy, as well-anchored expectations promote price stability and reduce disinflation costs. However, heightened uncertainty and global disruptions make maintaining expectations near the target increasingly difficult. Macroeconomic agents form expectations based on policy signals and external shocks, with anchoring depending on both monetary authority credibility and agents' sensitivity to economic conditions. Understanding expectation formation across different groups is essential to assessing the resilience of inflation targeting framework and the extent to which policy influences long-term stability.

The case of Chile offers insights into inflation expectation dynamics under an inflation-targeting regime. Using a measure of steady-state expectations, this study analyses expectation formation through linear, non-linear, and binary-outcome models. Time-series estimates confirm that forecasting errors and deviations from BCCh forecasts significantly influence long-term expectations, while uncertainty also plays a role, particularly in higher-uncertainty regimes, as shown by simple switching regressions. Binary-outcome Probit models further confirm that monetary policy instruments and uncertainty contribute to deviations, even when persistence effects are disregarded.

Expectations are not formed purely in a backward-looking manner but adjust dynamically to incoming data and economic risks, with higher uncertainty amplifying deviations. Financial market participants exhibit stronger anchoring, while experts and corporate sector respondents are more responsive to macroeconomic fluctuations. These findings highlight the need for consistent and accurate official inflation forecasts to sustain confidence. While monetary policy remains vital, its effectiveness depends on broader economic conditions. Importantly, anchoring can persist despite exogenous influences if the Central Bank retains sufficient influence over expectations. Mitigating uncertainty is therefore essential for preserving anchored inflation expectations and reinforcing macroeconomic stability.

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A Summary of descriptive statistics

Table A1: Descriptive statistics of the time-series data (*)

	Mean	Median	St. dev.	Max.	Min.	P25	P75	P-P
	Full sample: 2001.9-2024.12 (280 observations)							
Inflation	3.84	3.10	2.71	14.10	-2.27	2.42	4.46	0.077
EEE: Infl. 11 [All]	3.26	3.00	0.84	7.30	2.00	2.90	3.40	0.054
EEE: Infl. 23 [All]	3.06	3.00	0.19	4.00	2.80	3.00	3.00	0.011
EEE: Infl. 11 [Experts]	3.30	3.00	0.89	8.10	1.65	2.85	3.50	0.044
EEE: Infl. 23 [Experts]	3.09	3.00	0.25	4.20	2.55	3.00	3.00	0.004
EEE: Infl. 11 [Financial mkt.]	3.22	3.00	0.82	7.15	1.95	2.80	3.30	0.041
EEE: Infl. 23 [Financial mkt.]	3.05	3.00	0.16	4.00	2.80	3.00	3.00	0.001
EEE: Infl. 11 [Corporate]	3.30	3.05	0.84	7.30	1.50	2.90	3.43	0.039
EEE: Infl. 23 [Corporate]	3.08	3.00	0.22	4.25	2.90	3.00	3.00	0.009
IPoM: Infl. *T*	3.68	3.10	1.99	12.34	-0.80	2.70	4.20	0.077
IPoM: Infl. *T+1*	3.07	3.00	0.35	4.90	2.30	2.91	3.10	0.077
IEC	158.9	127.9	95.1	446.1	39.3	90.0	206.1	0.000
EPU	141.6	115.3	87.1	454.6	31.6	79.9	178.3	0.000
GPR	110.0	95.6	51.5	512.5	58.4	83.1	120.4	0.000
	Pre-COVID-19 sample: 2001.9-2020.2 (222 observations)							
Inflation	3.19	2.85	1.98	9.85	-2.27	2.19	4.00	-
EEE: Infl. 11 [All]	3.07	3.00	0.53	6.00	2.00	2.80	3.20	-
EEE: Infl. 23 [All]	3.03	3.00	0.13	3.90	2.80	3.00	3.00	-
EEE: Infl. 11 [Experts]	3.09	3.00	0.56	5.50	1.65	2.80	3.30	-
EEE: Infl. 23 [Experts]	3.04	3.00	0.16	4.00	2.55	3.00	3.00	-
EEE: Infl. 11 [Financial mkt.]	3.04	3.00	0.54	6.00	1.95	2.80	3.20	-
EEE: Infl. 23 [Financial mkt.]	3.03	3.00	0.12	3.95	2.90	3.00	3.00	-
EEE: Infl. 11 [Corporate]	3.10	3.00	0.51	5.50	1.50	2.90	3.25	-
EEE: Infl. 23 [Corporate]	3.04	3.00	0.13	3.90	2.90	3.00	3.00	-
IPoM: Infl. *T*	3.25	3.00	1.39	8.50	-0.80	2.60	3.70	-
IPoM: Infl. *T+1*	3.04	3.04	0.35	4.90	2.30	2.90	3.05	-
IEC	116.0	116.0	58.1	413.4	39.3	81.9	138.8	-
EPU	108.0	108.0	48.7	283.7	31.6	70.9	132.3	-
GPR	108.8	108.8	53.2	512.5	58.4	83.4	115.1	-

(*) All series, except IEC, EPU, and GPR, are expressed as percentages, representing the year-on-year variation of the Consumer Price Index (CPI). The IEC, EPU, and GPR 100-base indices: IEC: 100=2007.1-2016.10 average, EPU: 100=1993.1-2016.10 average, and GPR: 100=1985.1-2019.12 average. "PNN" denotes the "NN"-th percentile. "P-P" refers to the *p*-value of the null hypothesis in the Phillips and Perron (1988) test (NH: Series has a unit root). Sources: Central Bank of Chile, National Statistics Institute, Centre for Economic and Social Policies (CLAPES UC; Cerda, Silva, and Valente, 2017) and Caldara and Iacoviello (2022) (data retrieved from https://www.MatteoIacoviello.com/GPR.htm).

B Analysis of uncertainty and geopolitical shocks on actual inflation

This annex presents an impulse response function estimated via a vector autoregression (VAR) model, aimed at providing a numerical assessment of the effects of uncertainty and geopolitical shocks on inflation. The exercise serves to illustrate how the impact of these shocks evolves and dissipates over time, despite their inflationary effect within two years after the shock. This pattern may explain why the coefficients of the indices are positive on their own but turn negative when interacted with inflation.

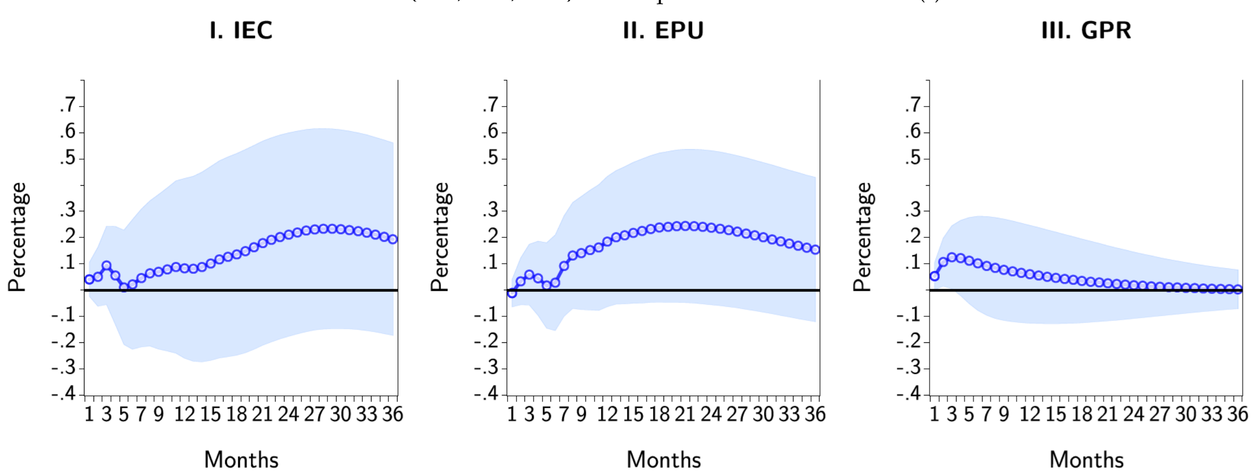
The stationary VAR model in equation (B1) is estimated using an identification scheme in which the exogenous index ($Index_t$) is ordered first. This allows it to influence the year-on-year copper price (p_t^{Cu}), both of which affect the monthly return of the nominal exchange rate CLP/USD (q_t), with all variables jointly determining inflation (π_t):

$$\underbrace{\begin{bmatrix} Index_t \\ p_t^{Cu} \\ q_t \\ \pi_t \end{bmatrix}}_{=\mathbf{Y}_t} = \underbrace{\begin{bmatrix} \alpha^1 \\ \alpha^2 \\ \alpha^3 \\ \alpha^4 \end{bmatrix}}_{=\boldsymbol{\alpha}} + \underbrace{\begin{bmatrix} \rho^1 & 0 & 0 & 0 \\ \delta^1 & \delta^2 & 0 & 0 \\ \beta^1 & \beta^2 & \beta^3 & 0 \\ \gamma^1 & \gamma^2 & \gamma^3 & \gamma^4 \end{bmatrix}}_{=\boldsymbol{\Theta}^1} \underbrace{\begin{bmatrix} Index_{t-1} \\ p_{t-1}^{Cu} \\ q_{t-1} \\ \pi_{t-1} \end{bmatrix}}_{=\mathbf{Y}_{t-1}} + \underbrace{\begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \\ \varepsilon_t^3 \\ \varepsilon_t^4 \end{bmatrix}}_{=\boldsymbol{\varepsilon}_t}, \tag{B1}$$

where the set ε_t^i represents white noise disturbances. This specification controls for external inflationary shocks through the exchange rate channel. The lag length of the VAR is selected using the Akaike Information Criterion, resulting in 6 lags for IEC (*i.e.*, $\{\boldsymbol{\Theta}^1, ..., \boldsymbol{\Theta}^6\}$), 6 for EPU, and 2 for GPR. The estimation sample spans from 2001.9 to 2024.12 (280 observations). Results are displayed in Figure B1.

The findings suggest a hump-shaped inflationary response following the shocks. Specifically, for IEC and EPU, inflation responds weakly at first, then increases steadily over approximately two years before gradually fading. In the case of GPR, although the overall pattern is similar, the magnitude of the response is lower, and the peak occurs much earlier—around the third month following the shock.This implies that, when forming expectations, agents take the immediate shock into account in their forecasts; however, this effect is moderated when interacted with the inflation rate, suggesting that these shocks are absorbed within the policy horizon.

Figure B1: Impulse response function estimates for a one-standard-deviation shock in {IEC,EPU,GPR} and response of actual inflation (*)



(*) Impulse response to Cholesky one-standard-deviation innovations (adjusted for degrees of freedom). The 95% confidence intervals are computed using Monte Carlo standard errors with 5000 replications. Full sample: 2001.9–2024.12 (280 observations). Source: Author's calculations based on data from the Central Bank of Chile and the National Statistics Institute.

C Results of the experts' inflation expectations model

Table C1. Time-series models for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable: π_t^*											
π_{t-1}^*	1.197***	1.260***	0.915***	0.897***	0.922***	0.918***	0.918***	0.938***	0.920***	0.932***	0.922***
	(0.154)	(0.138)	(0.043)	(0.043)	(0.043)	(0.039)	(0.038)	(0.038)	(0.038)	(0.036)	(0.036)
π_{t-2}^*	-0.490***	-0.521***	-	-	-	-	-	-	-	-	-
	(0.111)	(0.117)	-	-	-	-	-	-	-	-	-
π_T^{IPoM}	0.192	0.173***	-	-	-	-	-	-	-	-	-
	(0.199)	(0.094)	-	-	-	-	-	-	-	-	-
π_{T+1}^{IPoM}	-0.029	-	-	-	-	-	-	-	-	-	-
	(0.140)	-	-	-	-	-	-	-	-	-	-
$e_{t\|t+11}^{EEE}$	-0.039	0.015**	0.023***	0.025***	0.022***	0.021***	0.021***	0.019***	0.024***	0.024***	0.022***
	(0.235)	(0.012)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$e_{t\|t+23}^{EEE}$	0.054	-	-	-	-	-	-	-	-	-	-
	(0.239)	-	-	-	-	-	-	-	-	-	-
$e_{t\|T}^{IPoM}$	0.244***	0.233***	0.058**	0.056**	0.058**	0.053**	0.053**	0.057***	0.041**	0.048**	0.046**
	(0.203)	(0.106)	(0.021)	(0.021)	(0.021)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
e_t^{Target}	-0.019	-	-	-	-	-	-	-	-	-	-
	(0.022)	-	-	-	-	-	-	-	-	-	-
$IEC_{t-j,j=\{1,2,3\}}$		-	-0.001	-0.032	0.010	-	-	-	-	-	-
	-	-	(0.036)	(0.041)	(0.035)	-	-	-	-	-	-
$IEC_{t-1}\cdot\pi_t$	-	-	0.003	0.005	0.002	-	-	-	-	-	-
	-	-	(0.005)	(0.006)	(0.005)	-	-	-	-	-	-
$EPU_{t-j,j=\{1,2,3\}}$		-	-	-	-	0.005	0.002	0.045	-	-	-
	-	-	-	-	-	(0.036)	(0.036)	(0.034)	-	-	-
$EPU_{t-1}\cdot\pi_t$	-	-	-	-	-	0.002	0.002	0.0005	-	-	-
	-	-	-	-	-	(0.005)	(0.004)	(0.004)	-	-	-
$GPR_{t-j,j=\{1,2,3\}}$		-	-	-	-	-	-	-	0.091**	0.057	-0.010
	-	-	-	-	-	-	-	-	(0.049)	(0.042)	(0.032)
$GPR_{t-6}\cdot\pi_t$	-	-	-	-	-	-	-	-	0.0003	0.0009	0.002
	-	-	-	-	-	-	-	-	(0.005)	(0.005)	(0.005)
Constant	-0.484**	-0.509***	0.012	0.042	0.001	0.002	0.004	-0.038	-0.079	-0.046	0.021
	(0.770)	(0.289)	(0.044)	(0.046)	(0.044)	(0.039)	(0.039)	(0.040)	(0.057)	(0.050)	(0.042)
No. obs.	76	86	70	70	70	86	86	86	86	86	86
Adj. R-sq.	0.917	0.9180	0.902	0.898	0.903	0.909	0.909	0.913	0.912	0.908	0.908
AR terms	No	No	1	1	1	1	1	1	1	1	1
Est. method	OLS/NW	OLS/NW	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "OLS/NW" = Ordinary Least Squares with Newey-West corrected standard deviations. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12.

Source: Author's elaboration.

Table C2. Simple switching regression estimates for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: π_t^*									
Regime 1: Lower uncertainty, stablised geopolitical tensions									
Index:	IEC $\{i=t-3, j=t-1\}$			EPU $\{i=t-3, j=t-1\}$			GPR $\{i=t-3, j=t-6\}$		
π_{t-1}^*	0.837***	0.843***	0.837***	0.793***	0.794***	0.788***	0.807***	0.807***	0.810***
	(0.056)	(0.053)	(0.054)	(0.115)	(0.114)	(0.096)	(0.031)	(0.031)	(0.030)
$Index_i$	-0.021	-0.003	-0.019	0.105**	0.104**	-0.014	-0.066**	-0.066**	-0.068**
	(0.016)	(0.016)	(0.017)	(0.053)	(0.052)	(0.015)	(0.027)	(0.027)	(0.027)
$Index_j \cdot \pi_t$	0.003	-0.002	0.002	-0.003	-0.003	0.006***	0.005*	0.005*	0.005*
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regime 2: Higher uncertainty, heightened geopolitical tensions									
π_{t-1}^*	0.981***	0.832***	0.978***	0.804***	0.805***	0.972***	1.065***	1.065***	1.073***
	(0.121)	(0.108)	(0.126)	(0.069)	(0.069)	(0.157)	(0.068)	(0.068)	(0.066)
$Index_i$	0.094	0.095*	0.087	-0.005	-0.005	0.121*	0.235**	0.236**	0.237**
	(0.070)	(0.054)	(0.066)	(0.014)	(0.014)	(0.064)	(0.094)	(0.094)	(0.092)
$Index_j \cdot \pi_t$	-0.007	-0.004	-0.008	0.001	0.001	-0.009*	-0.023***	-0.023***	-0.024***
	(0.005)	(0.004)	(0.005)	(0.002)	(0.002)	(0.005)	(0.009)	(0.009)	(0.008)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common regressors									
$e_{t\|t+11}^{EEE}$	0.008	0.007	0.006	0.005	0.005	0.004	0.005	0.005	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)
Probabilities parameters (Logit estimates)									
$IEC_{\{0,1\}}$	0.030	0.467	-0.846	-0.338	-0.332	-0.714	-0.112	-0.118	-0.587
	(0.673)	(0.919)	(0.546)	(0.845)	(0.827)	(0.498)	(0.640)	(0.626)	(0.474)
$EPU_{\{0,1\}}$	-1.332**	-1.938**	-	1.901**	1.896**	-	-0.831	-0.832	-
	(0.663)	(0.935)	-	(0.858)	(0.844)	-	(0.643)	(0.638)	-
$GPR_{\{0,1\}}$	-0.142	-	-	-0.052	-	-	0.066	-	-
	(0.573)	-	-	(0.689)	-	-	(0.507)	-	-
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	212	212	212	278	278	278	278	278	278
Std. dev. of regression	0.191	0.191	0.193	0.1675	0.166	0.175	0.166	0.166	0.168
Log likelihood	145.4	145.9	142.9	150.2	150.2	149.0	153.3	153.3	152.3
Est. method	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Table C3. Probit marginal effects estimates for $\pi^*_{\{0,1\}}$ (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent variable: $\pi^*_{\{0,1\}}$														
π_T^{IPoM}	0.772***	0.984***	0.581**	0.618***	0.690***	1.067***	0.867***	1.009***	0.804***	1.135***	1.136***	1.485***	0.944***	1.550***
	(0.280)	(0.134)	(0.228)	(0.232)	(0.134)	(0.150)	(0.307)	(0.313)	(0.171)	(0.161)	(0.363)	(0.364)	(0.171)	(0.230)
π_{T+1}^{IPoM}	0.425*	-	0.903**	0.920**	0.900**	-	0.513**	0.490**	0.513***	-	0.744**	0.719***	0.714***	-
	(0.234)	-	(0.397)	(0.387)	(0.397)	-	(0.247)	(0.233)	(0.248)	-	(0.255)	(0.229)	(0.255)	-
e_{t+11}^{EEE}	-0.018	0.011	-0.108	-0.195	0.017	0.007	0.093	0.133	0.020	0.008	0.227	0.266	0.041**	0.019
	(0.244)	(0.016)	(0.248)	(0.272)	(0.014)	(0.017)	(0.292)	(0.293)	(0.016)	(0.017)	(0.295)	(0.271)	(0.018)	(0.016)
e_{t+23}^{EEE}	0.037	-	0.126	0.212	-	-	-0.073	-0.117	-	-	-0.184	-0.225	-	-
	(0.244)	-	(0.249)	(0.272)	-	-	(0.293)	(0.294)	-	-	(0.294)	(0.269)	-	-
e_T^{IPoM}	0.705**	0.874***	0.539**	0.583**	0.644***	0.956***	0.790**	0.971***	0.729***	1.083***	1.029***	1.399***	0.841***	1.440***
	(0.285)	(0.182)	(0.249)	(0.250)	(0.165)	(0.192)	(0.326)	(0.346)	(0.213)	(0.217)	(0.366)	(0.370)	(0.184)	(0.255)
e^{Target}	-0.105***	-0.131***	-0.094***	-0.124**	-0.087	-0.159***	-0.102***	-0.122***	-0.107***	-0.175***	-0.090***	-0.197***	-0.103***	-0.324***
	(0.034)	(0.034)	(0.036)	(0.048)	(0.029)	(0.045)	(0.039)	(0.042)	(0.034)	(0.040)	(0.038)	(0.046)	(0.034)	(0.063)
$IEC_{\{0,1\}}$	-	-	0.090	-	0.096	-0.056	-	-	-	-	-	-	-	-
	-	-	(0.084)	-	(0.086)	(0.197)	-	-	-	-	-	-	-	-
$IEC_{\{0,1\}} \cdot \pi_t$	-	-	-	0.034	-	0.045	-	-	-	-	-	-	-	-
	-	-	-	(0.024)	-	(0.055)	-	-	-	-	-	-	-	-
$EPU_{\{0,1\}}$	-	-	-	-	-	-	0.073	-	0.070	-0.242	-	-	-	-
	-	-	-	-	-	-	(0.106)	-	(0.108)	(0.229)	-	-	-	-
$EPU_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	0.042	-	0.106*	-	-	-	-
	-	-	-	-	-	-	-	(0.030)	-	(0.063)	-	-	-	-
$GPR_{\{0,1\}}$	-	-	-	-	-	-	-	-	-	-	0.368**	-	0.343**	-0.532***
	-	-	-	-	-	-	-	-	-	-	(0.174)	-	(0.169)	(0.182)
$GPR_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	-	-	-	-	0.095***	-	0.179***
	-	-	-	-	-	-	-	-	-	-	-	(0.026)	-	(0.048)
No. obs.	77	87	61	61	61	71	70	70	70	80	70	70	70	70
Pseudo R-sq.	0.4439	0.4261	0.5554	0.5671	0.5535	0.4745	0.4831	0.4980	0.4825	0.4755	0.5297	0.5702	0.5265	0.5268
Est. method	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML

(†) Delta-method-based standard deviation in parentheses. "ML" = Maximum likelihood estimation method. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

D Results of the financial market participants' inflation expectations model

Table D1. Time-series models for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable: π_t^*											
π_{t-1}^*	1.014***	1.197***	1.017***	1.015***	1.000***	1.005***	1.000***	1.000***	0.999***	0.986***	0.984***
	(0.154)	(0.138)	(0.043)	(0.043)	(0.043)	(0.039)	(0.038)	(0.038)	(0.038)	(0.036)	(0.036)
π_{t-2}^*	-0.246**	-0.265**	-	-	-	-	-	-	-	-	-
	(0.111)	(0.117)	-	-	-	-	-	-	-	-	-
π_T^{IPoM}	-0.144	-0.022	-	-	-	-	-	-	-	-	-
	(0.199)	(0.094)	-	-	-	-	-	-	-	-	-
π_{T+1}^{IPoM}	0.132	-	-	-	-	-	-	-	-	-	-
	(0.140)	-	-	-	-	-	-	-	-	-	-
$e_{t\|t+11}^{EEE}$	-0.327	0.012	0.028***	0.027***	0.031***	0.027***	0.026***	0.028***	0.020***	0.021***	0.021***
	(0.235)	(0.012)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$e_{t\|t+23}^{EEE}$	0.347	-	-	-	-	-	-	-	-	-	-
	(0.239)	-	-	-	-	-	-	-	-	-	-
$e_{t\|T}^{IPoM}$	-0.134	-0.033	-0.005	-0.001	-0.001	-0.006	0.0003	0.002	-0.0008	-0.005	-0.005
	(0.203)	(0.106)	(0.021)	(0.021)	(0.021)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
e_t^{Target}	-0.017	-	-	-	-	-	-	-	-	-	-
	(0.017)	-	-	-	-	-	-	-	-	-	-
$IEC_{t-j\prime j=\{1,2,3\}}$		-	0.072*	0.069*	0.036	-	-	-	-	-	-
	-	-	(0.036)	(0.041)	(0.035)	-	-	-	-	-	-
$IEC_{t-1} \cdot \pi_t$	-	-	-0.017***	-0.017***	-0.013**	-	-	-	-	-	-
	-	-	(0.005)	(0.006)	(0.005)	-	-	-	-	-	-
$EPU_{t-j,j=\{1,2,3\}}$		-	-	-	-	0.066*	0.067*	0.068**	-	-	-
	-	-	-	-	-	(0.036)	(0.036)	(0.034)	-	-	-
$EPU_{t-1} \cdot \pi_t$	-	-	-	-	-	-0.015***	-0.015***	-0.014***	-	-	-
	-	-	-	-	-	(0.005)	(0.004)	(0.004)	-	-	-
$GPR_{t-j,j=\{1,2,3\}}$		-	-	-	-	-	-	-	-0.049	-0.012	0.008
	-	-	-	-	-	-	-	-	(0.049)	(0.042)	(0.032)
$GPR_{t-6} \cdot \pi_t$	-	-	-	-	-	-	-	-	-0.018***	-0.018***	-0.019**
	-	-	-	-	-	-	-	-	(0.005)	(0.005)	(0.005)
$Constant$	0.041	0.064	-0.010	-0.002	0.023	-0.011	-0.001	-0.018	0.116**	0.077	0.057
	(0.770)	(0.289)	(0.044)	(0.046)	(0.044)	(0.039)	(0.039)	(0.040)	(0.057)	(0.050)	(0.042)
No. obs.	76	86	70	70	70	86	86	86	86	86	86
Adj. R-sq.	0.936	0.931	0.964	0.962	0.959	0.959	0.958	0.957	0.961	0.959	0.959
AR terms	No	No	1	1	1	1	1	1	1	1	1
Est. method	OLS/NW	OLS/NW	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "OLS/NW" = Ordinary Least Squares with Newey-West corrected standard deviations. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12.

Source: Author's elaboration.

Table D2. Simple switching regression estimates for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: π_t^*									
Regime 1: Lower uncertainty, stablised geopolitical tensions									
Index:	IEC $\{i=t-3, j=t-1\}$			EPU $\{i=t-3, j=t-1\}$			GPR $\{i=t-3, j=t-6\}$		
π_{t-1}^*	0.840***	0.833***	0.791***	1.533***	0.521***	0.821***	1.686***	0.778***	0.779***
	(0.043)	(0.065)	(0.116)	(0.115)	(0.126)	(0.049)	(0.171)	(0.069)	(0.068)
$Index_i$	0.004	0.002	0.016	-0.051	0.280***	0.025	-0.368	-0.040	-0.048
	(0.017)	(0.016)	(0.019)	(0.088)	(0.076)	(0.016)	(0.275)	(0.048)	(0.046)
$Index_j \cdot \pi_t$	-0.002	0.003	0.002	-0.012	0.003	-0.001	-0.022	0.011	0.011
	(0.002)	(0.003)	(0.003)	(0.008)	(0.007)	(0.002)	(0.014)	(0.008)	(0.008)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regime 2: Higher uncertainty, heightened geopolitical tensions									
π_{t-1}^*	0.489**	0.562***	0.514***	0.746***	0.751***	0.573***	0.745***	0.781***	0.781***
	(0.192)	(0.100)	(0.114)	(0.054)	(0.091)	(0.127)	(0.069)	(0.098)	(0.093)
$Index_i$	0.220**	0.272***	0.289***	0.026	0.038**	0.383***	-0.054	0.283	0.286
	(0.107)	(0.091)	(0.103)	(0.017)	(0.015)	(0.075)	(0.045)	(0.208)	(0.200)
$Index_j \cdot \pi_t$	0.020	-0.007	-0.021**	-0.004*	0.004	-0.009	-0.008**	-0.013	-0.013
	(0.016)	(0.009)	(0.010)	(0.002)	(0.003)	(0.008)	(0.003)	(0.016)	(0.014)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common regressors									
$e_{t\|t+11}^{EEE}$	0.019***	0.018***	0.014*	0.024***	0.018***	0.020***	0.019**	0.018***	0.016***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)
Probabilities parameters (Logit estimates)									
$IEC_{\{0,1\}}$	0.298	0.259	-0.929	-0.629	-0.742	-0.647	-0.805	0.215	-1.099**
	(0.889)	(0.777)	(0.565)	(0.977)	(0.783)	(0.574)	(0.857)	(0.739)	(0.510)
$EPU_{\{0,1\}}$	-1.384	-2.187***	-	1.994**	2.213***	-	2.080**	-2.051	-
	(0.962)	(0.789)	-	(0.886)	(0.781)	-	(0.934)	(0.750)	-
$GPR_{\{0,1\}}$	0.028	-	-	-0.231	-	-	-0.387	-	-
	(0.889)	-	-	(0.702)	-	-	(0.894)	-	-
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	212	212	212	278	278	278	278	278	278
Std. dev. of regression	0.251	0.262	0.285	0.210	0.221	0.223	0.208	0.225	0.225
Log likelihood	115.7	114.3	110.1	123.7	114.9	110.0	119.7	115.1	110.0
Est. method	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Table D3. Probit marginal effects estimates for $\pi^*_{\{0,1\}}$ (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent variable: $\pi^*_{\{0,1\}}$														
π_T^{IPoM}	-0.133	0.986***	-0.031	0.002	0.691***	1.070***	-0.372	-0.314	0.808***	1.142***	-0.090	0.380	0.939***	1.551***
	(0.455)	(0.134)	(0.496)	(0.483)	(0.135)	(0.150)	(0.566)	(0.650)	(0.172)	(0.161)	(0.566)	(0.581)	(0.170)	(0.229)
π_{T+1}^{IPoM}	0.282	-	0.678*	0.670*	0.905**	-	0.277	0.247	0.512**	-	0.473	0.496*	0.709***	-
	(0.216)	-	(0.358)	(0.346)	(0.399)	-	(0.241)	(0.237)	(0.252)	-	(0.290)	(0.270)	(0.257)	-
e_{t+11}^{EEE}	-1.037**	0.009	-0.742	-0.814	0.018	0.006	-1.318**	-1.396**	0.019	0.005	-1.112*	-0.901	0.039**	0.018
	(0.494)	(0.016)	(0.487)	(0.502)	(0.014)	(0.017)	(0.613)	(0.701)	(0.016)	(0.017)	(0.591)	(0.590)	(0.018)	(0.016)
e_{t+23}^{EEE}	1.052**	-	0.756	0.825*	-	-	1.330**	1.405**	-	-	1.142*	0.930	-	-
	(0.494)	-	(0.485)	(0.498)	-	-	(0.615)	(0.704)	-	-	(0.587)	(0.585)	-	-
e_T^{IPoM}	-0.212	0.874***	-0.072	-0.031	0.645***	0.959***	-0.451	-0.362	0.734***	1.091***	-0.199	0.298	0.836***	1.440***
	(0.466)	(0.182)	(0.515)	(0.498)	(0.164)	(0.193)	(0.591)	(0.690)	(0.214)	(0.217)	(0.570)	(0.588)	(0.182)	(0.254)
e^{Target}	-0.091***	-0.122***	-0.071**	-0.093**	-0.088***	-0.160***	-0.094**	-0.121***	-0.110***	-0.177***	-0.094**	-0.187***	-0.106***	-0.327***
	(0.034)	(0.034)	(0.032)	(0.036)	(0.028)	(0.045)	(0.038)	(0.041)	(0.034)	(0.039)	(0.039)	(0.050)	(0.034)	(0.063)
$IEC_{\{0,1\}}$	-	-	0.092	-	0.095	-0.055	-	-	-	-	-	-	-	-
	-	-	(0.082)	-	(0.086)	(0.199)	-	-	-	-	-	-	-	-
$IEC_{\{0,1\}} \cdot \pi_t$	-	-	-	0.033	-	0.045	-	-	-	-	-	-	-	-
	-	-	-	(0.023)	-	(0.055)	-	-	-	-	-	-	-	-
$EPU_{\{0,1\}}$	-	-	-	-	-	-	0.085	-	0.071	-0.243	-	-	-	-
	-	-	-	-	-	-	(0.096)	-	(0.109)	(0.229)	-	-	-	-
$EPU_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	0.043	-	0.107*	-	-	-	-
	-	-	-	-	-	-	-	(0.028)	-	(0.063)	-	-	-	-
$GPR_{\{0,1\}}$	-	-	-	-	-	-	-	-	-	-	0.288*	-	0.333**	-0.533***
	-	-	-	-	-	-	-	-	-	-	(0.171)	-	(0.170)	(0.183)
$GPR_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	-	-	-	-	0.082***	-	0.179***
	-	-	-	-	-	-	-	-	-	-	-	(0.031)	-	(0.049)
No. obs.	77	87	61	61	61	71	70	70	70	80	70	70	70	80
Pseudo R-sq.	0.4679	0.4251	0.5677	0.5787	0.5535	0.4740	0.5172	0.5346	0.4808	0.4746	0.5491	0.5793	0.5226	0.5249
Est. method	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML

(†) Delta-method-based standard deviation in parentheses. "ML" = Maximum likelihood estimation method. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

E Results of the corporate sector participants' inflation expectations model

Table E1. Time-series models for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable: π_t^*											
π_{t-1}^*	0.996***	1.112***	0.966***	0.961***	0.956***	0.957***	0.956***	0.962***	0.976***	0.982***	0.975***
	(0.210)	(0.186)	(0.050)	(0.051)	(0.050)	(0.045)	(0.045)	(0.046)	(0.038)	(0.037)	(0.038)
π_{t-2}^*	-0.154	-0.223	-	-	-	-	-	-	-	-	-
	(0.246)	(0.242)	-	-	-	-	-	-	-	-	-
π_T^{IPoM}	0.095	0.031	-	-	-	-	-	-	-	-	-
	(0.125)	(0.056)	-	-	-	-	-	-	-	-	-
π_{T+1}^{IPoM}	-0.049	-	-	-	-	-	-	-	-	-	-
	(0.137)	-	-	-	-	-	-	-	-	-	-
$e_{t\|t+11}^{EEE}$	-0.045	0.016**	0.020***	0.020***	0.020***	0.018***	0.018***	0.018***	0.016***	0.017***	0.016***
	(0.101)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$e_{t\|t+23}^{EEE}$	0.061	-	-	-	-	-	-	-	-	-	-
	(0.105)	-	-	-	-	-	-	-	-	-	-
$e_{t\|T}^{IPoM}$	0.116	0.061	0.032	0.033	0.033	0.027	0.028	0.029	0.007	0.010	0.010
	(0.112)	(0.064)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.016)
e_t^{Target}	-0.029	-	-	-	-	-	-	-	-	-	-
	(0.022)	-	-	-	-	-	-	-	-	-	-
$IEC_{t-j,j=\{1,2,3\}}$		-	0.002	-0.009	-0.017	-	-	-	-	-	-
	-	-	(0.034)	(0.039)	(0.033)	-	-	-	-	-	-
$IEC_{t-1} \cdot \pi_t$	-	-	-0.002	-0.001	0.0001	-	-	-	-	-	-
	-	-	(0.005)	(0.005)	(0.005)	-	-	-	-	-	-
$EPU_{t-j,j=\{1,2,3\}}$		-	-	-	-	0.008	0.007	0.019	-	-	-
	-	-	-	-	-	(0.033)	(0.034)	(0.032)	-	-	-
$EPU_{t-1} \cdot \pi_t$	-	-	-	-	-	-0.002	-0.002	-0.003	-	-	-
	-	-	-	-	-	(0.004)	(0.004)	(0.004)	-	-	-
$GPR_{t-j,j=\{1,2,3\}}$		-	-	-	-	-	-	-	0.040	0.057	0.049*
	-	-	-	-	-	-	-	-	(0.051)	(0.038)	(0.028)
$GPR_{t-6} \cdot \pi_t$	-	-	-	-	-	-	-	-	-0.012***	-0.012***	-0.012***
	-	-	-	-	-	-	-	-	(0.004)	(0.004)	(0.004)
Constant	-0.131	-0.092	0.014	0.024	0.032	0.001	0.002	-0.010	0.001	-0.017	-0.011
	(0.328)	(0.170)	(0.043)	(0.044)	(0.041)	(0.036)	(0.036)	(0.037)	(0.054)	(0.044)	(0.037)
No. obs.	76	86	70	70	70	86	86	86	86	86	86
Adj. R-sq.	0.922	0.924	0.943	0.943	0.944	0.943	0.943	0.943	0.936	0.935	0.942
AR terms	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Est. method	OLS/NW	OLS/NW	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "OLS/NW" = Ordinary Least Squares with Newey-West corrected standard deviations. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12.

Source: Author's elaboration.

Table E2. Simple switching regression estimates for π_t^* (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: π_t^*									
Regime 1: Lower uncertainty, stablised geopolitical tensions									
Index:	IEC $\{i=t-3, j=t-1\}$			EPU $\{i=t-3, j=t-1\}$			GPR $\{i=t-3, j=t-6\}$		
π_{t-1}^*	1.463***	0893***	0.900***	1.357***	0.870***	0.868***	0.875***	0.876***	0.932***
	(0.102)	(0.026)	(0.035)	(0.104)	(0.031)	(0.031)	(0.031)	(0.031)	(0.016)
$Index_i$	0.076	-0.015	-0.016	0.075	0.002	0.001	-0.038	-0.035	-0.040
	(0.056)	(0.014)	(0.014)	(0.067)	(0.120)	(0.012)	(0.031)	(0.031)	(0.025)
$Index_j \cdot \pi_t$	-0.032***	0.000	0.000	-0.025***	-0.001	0.000	-0.004	-0.003	0.004**
	(0.007)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regime 2: Higher uncertainty, heightened geopolitical tensions									
π_{t-1}^*	0.892***	1.462***	1.610***	0.866***	1.363***	1.361***	1.165***	1.159***	0.829***
	(0.026)	(0.101)	(0.153)	(0.032)	(0.102)	(0.099)	(0.102)	(0.100)	(0.062)
$Index_i$	-0.015	0.074	0.324***	0.001	0.070	0.072	-0.041	-0.044	0.561***
	(0.014)	(0.052)	(0.068)	(0.012)	(0.064)	(0.066)	(0.138)	(0.109)	(0.035)
$Index_j \cdot \pi_t$	0.000	-0.032***	-0.062***	0.000	-0.026***	-0.026***	-0.021*	-0.020*	-0.017
	(0.002)	(0.007)	(0.010)	(0.002)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)
AR terms	1	1	1	1	1	1	1	1	1
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common regressors									
$e_{t\|t+11}^{EEE}$	0.021***	0.021***	0.020***	0.020***	0.019***	0.020***	0.018***	0.018***	0.008***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Probabilities parameters (Logit estimates)									
$IEC_{\{0,1\}}$	0.292	-0.253	-0.474	0.272	-0.225	-0.673	-0.166	-0.131	-0.301
	(0.972)	(0.970)	(0.811)	(0.989)	(0.991)	(0.650)	(1.151)	(1.159)	(0.424)
$EPU_{\{0,1\}}$	0.709	-0.755	-	0.749	-0.804	-	-0.809	-0.857	-
	(1.025)	(1.015)	-	(0.981)	(0.980)	-	(1.102)	(1.099)	-
$GPR_{\{0,1\}}$	0.603	-	-	0.593	-	-	-0.699	-	-
	(0.810)	-	-	(0.882)	-	-	(1.071)	-	-
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	212	212	212	278	278	278	278	278	278
Std. dev. of regression	0.163	0.163	0.163	0.144	0.144	0.146	0.142	0.142	0.137
Log likelihood	174.9	174.4	167.1	176.4	176.0	175.2	174.0	173.4	171.8
Est. method	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH	BHHH

(†) Standard deviation in parentheses. "BHHH" = Berndt-Hall-Hall-Hausman estimation algorithm. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

Table E3. Probit marginal effects estimates for $\pi^*_{\{0,1\}}$ (†)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent variable: $\pi^*_{\{0,1\}}$														
π_T^{IPoM}	1.252***	0.983***	1.803***	1.917***	0.682***	1.068***	1.835***	1.844***	0.799***	1.131***	1.848***	1.912***	0.940***	1.547***
	(0.319)	(0.133)	(0.274)	(0.212)	(0.134)	(0.149)	(0.331)	(0.299)	(0.171)	(0.160)	(0.273)	(0.214)	(0.169)	(0.229)
π_{T+1}^{IPoM}	0.414*	-	1.025***	1.073***	0.904**	-	0.618**	0.574**	0.517**	-	0.762***	0.687***	0.714***	-
	(0.223)	-	(0.295)	(0.277)	(0.389)	-	(0.294)	(0.272)	(0.246)	-	(0.250)	(0.220)	(0.253)	-
e_{t+11}^{EEE}	0.618*	0.013	1.150***	1.148***	0.019	0.010	0.150***	1.082***	0.022	0.009	1.065***	0.950***	0.041**	0.020
	(0.349)	(0.015)	(0.293)	(0.242)	(0.013)	(0.016)	(0.338)	(0.316)	(0.016)	(0.016)	(0.271)	(0.232)	(0.018)	(0.015)
e_{t+23}^{EEE}	-0.607*	-	-1.156***	-1.151***	-	-	-1.146***	-1.080***	-	-	-1.033***	-0.924***	-	-
	(0.355)	-	(0.301)	(0.251)	-	-	(0.345)	(0.322)	-	-	(0.278)	(0.240)	-	-
e_T^{IPoM}	1.178***	0.874***	1.773***	1.899***	0.639***	0.959***	1.785***	1.823***	0.725***	1.078***	1.760***	1.855**	0.839***	1.438***
	(0.333)	(0.180)	(0.253)	(0.202)	(0.163)	(0.192)	(0.327)	(0.299)	(0.212)	(0.216)	(0.280)	(0.222)	(0.183)	(0.253)
e^{Target}	-0.071*	-0.130***	-0.067**	-0.095**	-0.086***	-0.159***	-0.075**	-0.095**	-0.107***	-0.175***	-0.071**	-0.149***	-0.104***	-0.324***
	(0.037)	(0.034)	(0.034)	(0.038)	(0.028)	(0.045)	(0.037)	(0.039)	(0.034)	(0.040)	(0.030)	(0.033)	(0.034)	(0.063)
$IEC_{\{0,1\}}$	-	-	0.171**	-	0.094	-0.067	-	-	-	-	-	-	-	-
	-	-	(0.067)	-	(0.085)	(0.198)	-	-	-	-	-	-	-	-
$IEC_{\{0,1\}} \cdot \pi_t$	-	-	-	0.053***	-	0.048	-	-	-	-	-	-	-	-
	-	-	-	(0.017)	-	(0.055)	-	-	-	-	-	-	-	-
$EPU_{\{0,1\}}$	-	-	-	-	-	-	0.104	-	0.068	-0.241	-	-	-	-
	-	-	-	-	-	-	(0.097)	-	(0.108)	(0.229)	-	-	-	-
$EPU_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	0.044	-	0.105*	-	-	-	-
	-	-	-	-	-	-	-	(0.029)	-	(0.063)	-	-	-	-
$GPR_{\{0,1\}}$	-	-	-	-	-	-	-	-	-	-	0.322*	-	0.342**	-0.532***
	-	-	-	-	-	-	-	-	-	-	(0.179)	-	(0.168)	(0.182)
$GPR_{\{0,1\}} \cdot \pi_t$	-	-	-	-	-	-	-	-	-	-	-	0.079***	-	0.180***
	-	-	-	-	-	-	-	-	-	-	-	(0.024)	-	(0.048)
No. obs.	77	87	61	61	61	71	70	70	70	80	70	70	70	80
Pseudo R-sq.	0.4777	0.4272	0.6590	0.6738	0.5572	0.4760	0.5613	0.5721	0.4847	0.4762	0.5984	0.6333	0.5296	0.5285
Est. method	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML

(†) Delta-method-based standard deviation in parentheses. "ML" = Maximum likelihood estimation method. (*) $p<0.10$, (**) $p<0.05$, (***) $p<0.01$. Sample: 2001.9-2024.12. Source: Author's elaboration.

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