Long and Variable Lags in Argentina's Monetary Policy: Evidence from Disaggregated Price Indices

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Abstract

Using monthly data for 2016–2025, I identified unexpected policy innovations as residuals from a Taylor rule and estimated Local-Projection impulse responses for headline CPI, tradables/non-tradables, and nine disaggregated components, treating those innovations as monetary policy shocks. Tightening is no quick fix: a +10 pp policy-rate shock leaves monthly inflation above baseline for roughly two years and cumulates sizable price-level gains ($\approx$ 7–8 pp at one year, remaining positive at two to four years). Movements are faster and larger in tradables; services adjust more slowly, with wide heterogeneity across categories. Inference relies on heteroskedasticity- and autocorrelation-consistent (HAC) standard errors with wild-bootstrap checks. These patterns indicate long and variable lags in this setting; effective disinflation requires persistence and coordination with complementary instruments. Evidence suggests the monetary policy rate was either ineffective or not the right instrument to achieve price stability, perhaps favoring the choice of monetary-aggregate targeting for Argentina. I find early 90% significance for most series and zero-hit times clustering near two years.

Keywords: Monetary policy; Inflation dynamics; Local projections; Shock identification. **JEL:** E52; E31; C32; C54.

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1 Introduction

Argentina's recent monetary policy has been in the spotlight for its role in bringing down inflation from exceptional levels. Under the Milei administration, the Central Bank of the Argentine Republic (BCRA) has adopted a markedly contractionary stance—emphasizing tight liquidity conditions and control of the money supply in line with standard policy frameworks, a clear example of "dry" behavior.[2] These developments have been associated with a gradual, sustained deceleration in the inflation rate, challenging the view of an immediate response from prices to monetary policy innovations.

This paper tries to elucidate whether this phenomenon might be caused by "long and variable lags" in monetary policy (Friedman, 1961) and analyze some of its implications in the rules v. discretion discussion and the time inconsistency problem (Kydland and Prescott, 1977). I try to shed light on the transmission mechanisms of monetary policy to the economy in Argentina by analyzing how monetary policy shocks affect different components of the Consumer Price Index (CPI) using Local Projections (LPs) (Jordà, 2005).

Traditionally, the research question has been to determine how long changes in monetary policy take to affect the economy (e.g. how long the lag is), and how that time varies across episodes (e.g. how variable the lag is) (Friedman, 1961; Culbertson, 1961; Tanner, 1969). Even senior central bankers disagree on lag length: Atlanta Fed President Raphael Bostic points to roughly 18–24 months, whereas Federal Reserve Governor Christopher Waller argues for about 9–12 months (Dupor, 2023).

Monetary-policy shocks are constructed as residuals from a parsimonious Taylor-rule regression for the policy rate, conditioning on information known at $t-1$ (inflation expectations, the foreign exchange (FX) gap, and regime indicators). Residuals are interpreted as unanticipated innovations to the policy stance and rescaled to a 10% policy-rate increase for interpretability. Exchange-rate and risk-premium variables are excluded in baseline LPs to

[2] A "dry central banker" in the sense of Walsh (2017) is one who puts overriding weight on price stability and is willing to forgo short-run output gains.

avoid over-conditioning on transmission channels. Regime indicators—inflation targeting and capital controls—enter contemporaneously as intercept shifters; other controls are included only in lags to preserve predeterminedness.

I use monthly Argentine data from 2016 to 2025 and estimate separate LPs for headline inflation and a disaggregated set of CPI subindices (Food & Beverages, Apparel, Housing & Utilities, Household Equipment & Maintenance, Health Care, Transportation & Communications, Leisure, Education, Miscellaneous, plus Tradables and Non-tradables). Baseline results report non-cumulative (inflation) responses; and I also present cumulative responses that map into price-level effects.

Following Taylor (1995) I seek to identify the main variables responsible for the settings of monetary policy in Argentina. Does the economy react to shocks in interest or exchange rates? Does the credibility of the Central Bank or expectations about the future stance of monetary policy affect the outcome?

With that input, I then construct Impulse Response Functions (IRFs) of these shocks to the price level at different degrees of aggregation. These IRFs are valuable outputs as they provide a quick outlook of price dynamics following actions performed by monetary authorities.

My contributions are twofold. First, it builds a residual-based measure of monetary policy shocks for Argentina using a Taylor-rule framework. Second, it estimates LP impulse responses for headline CPI and a disaggregated set of components, documenting heterogeneity in timing and magnitude of effects.

At a high level, this paper finds modest on-impact effects that build over the first year, with clear cross-component heterogeneity: Tradables tend to adjust sooner and more sharply, while Non-tradables and regulated components react more gradually. Cumulative responses display widening confidence bands with the horizon, consistent with the aggregation of estimation uncertainty across horizons. The analysis is read against the monetary and FX timeline in Table 4 (inflation-targeting adoption, FX control episodes, IMF-supported tightening, and the post-2023 adjustment).

My estimates are conditional on the shock design, the information set used in the Taylor rule, and the LP control set. Structural breaks and concurrent policy packages remain a challenge; this paper addresses these with robustness checks (wild bootstrap bands, alternative windows) but do not claim full structural identification.

I operationalize "lag length" as the horizon of the peak absolute response and also report the earliest horizon at which responses are statistically different from zero at conventional levels. All figures use HAC bands (and wild-bootstrap bands as a robustness check with 999 replications at each horizon).

The rest of the paper proceeds as follows. Section 2 presents the literature review. Section 3 introduces the dataset, shock construction, and the local-projections specification; Section 4 presents the IRFs results; Section 5 concludes. After the References, Appendices provide data documentation and wild-bootstrap robustness checks.

2 Literature Review

There is substantial research and estimations about the monetary policy lag in the United States. However, there is a lack of information about Argentina. Literature about lags in the US begins with Friedman (1960, 1961) and Friedman and Schwartz (1963), whose central argument is that changes in monetary policy influence economic conditions only after a significant and variable lag. Friedman critiques the prevailing notion that monetary policy has immediate effects, instead showing that the lag between monetary actions and economic outcomes can range from months to over a year, with no precise predictability. In the study of 18 business cycles in the US, the author identified a 16-month lag in the effect of the rate of change in the stock of money to what was called "general business" (which would be nowadays equivalent to some measure of the employment level or GDP). Regarding the variability, he recorded an astonishing 6 to 29-month lagged effects in different business cycles.

Friedman's approach is particularly interesting for Argentina, as he considers the money supply, rather than interest rates, as the main driver of monetary policy. This idea, although old-fashioned in developed countries and stable developing ones, fits the Argentine case very well. However, given data and methodological limitations, I will resort to using the monetary policy rate assuming it is the primary instrument of monetary policy in the period under consideration and recognizing the strong link between administered rates and liquidity in the money market.

This work is related to three strands of research:

(i) Identified monetary policy shocks. A first strand estimates the causal effects of monetary policy using *identified* shocks rather than raw policy instruments. Ramey (2016) surveys the main strategies and clarifies the exogeneity conditions that guide our design. I follow the residualization logic of Romer and Romer (2004), adapting it to the Argentine setting by purging the policy-rate reaction to observable information that the Central Bank might use to set its policy (e.g., inflation expectations, output estimates) so that the resulting innovations can serve as shocks in our local projections. In an emerging-market context with thin derivatives markets and regime shifts, this work is closely aligned with Baioni (2024), who produces IRFs for narrative-based shocks and help guard against price-puzzle artifacts using a high-frequency approach in a SVAR setting and Local Projections for robustness checks. He finds that contractionary policy-rate raises headline inflation on impact consistent with models featuring interest-bearing central-bank liabilities.

(ii) Disaggregated prices and heterogeneous transmission. A second strand studies how monetary policy propagates across price subindices. Aruoba and Drechsel (2024) document heterogeneous and sometimes non-monotonic responses of Personal Consumption Expenditures (PCE)[3] subcomponents using local projections, together with re-aggregation

[3] The PCE price index—closely watched by the Federal Reserve—measures prices paid by consumers for goods and services; its core version excludes food and energy. Compared with CPI, PCE is broader and chain-weighted (Fisher), built from business-based NIPA data and includes third-party payments (e.g., employer health insurance), whereas CPI is a fixed-basket index for urban consumers derived from household surveys with a larger shelter weight and fewer revisions. PCE inflation typically runs slightly lower and smoother than CPI.

methods that quantify how composition drives the aggregate path. My work brings that disaggregated-LP perspective to Argentina's CPI: I estimate category-level IRFs to assess timing (lags to peak effects) and dynamics given publicly available information.

(iii) Local Projections methodology and inference. Methodologically, I rely on LPs (Jordà, 2005) with horizon-appropriate HAC inference and explicit controls, and I connect to recent results on the relation between LPs and VARs (Plagborg-Møller and Wolf, 2021) and on simple, robust LP inference (Olea and Plagborg-Møller, 2021). This work also draws on Jordà and Taylor (2024) for guidance on specification discipline (consistent controls across horizons, lag structure) and transparent reporting of uncertainty. A vital aspect of addressing this topic is uncertainty. Almuzara and Sancibrián (2024) address this issue extensively, showing how to interpret coefficients in a panel local projections, which is useful when applying the kind of analysis of Aruoba and Drechsel (2024). They advocate for the use of impulse-response functions to analyze the transmission of aggregate uncertainty to outcomes.

3 Methodology

3.1 Data and sample

I disaggregated Argentina's Consumer Price Index (CPI) into nine components inspired by the Classification of Individual Consumption According to Purpose (COICOP). Because the *Instituto Nacional de Estadística y Censos* (INDEC, Argentina's National Institute of Statistics and Censuses) experienced an intervention that undermined CPI quality during 2007–2015 and, subsequently, a temporary suspension of publications while methods were rebuilt (Dec. 2015 – mid-2016), I begin our sample in June 2016, when the national CPI was relaunched and later judged consistent with international standards by the IMF (censure lifted Nov. 9, 2016).

However, to maximize sample size, some data were obtained from the *Dirección de Estadísticas* *y Censos* of the province of San Luis (DEC, San Luis Statistics and Censuses Directorate) and thus a reaggregation of some components of the COICOP classification was necessary to ensure data continuity, using a regional weighted average. *Transportation* and *Communications* were merged and *Restaurants & Hotels* and *Recreation & Culture* were grouped under *Leisure*.

Inflation expectations are taken from the BCRA's *Relevamiento de Expectativas de Mercado* (REM). I use the survey's twelve-month-ahead CPI expectation, taking the last vintage available before the end of month t to avoid look-ahead bias.

I ensured stationarity of the series through log transformation and first or long differences where appropriate. All variables are expressed on a monthly basis. Sources and data availability are documented in Appendix A.

Table 1 documents how I define the monetary policy rate across changes in the BCRA's operational framework. Recording these regime shifts ensures a consistent benchmark for the policy rate throughout the sample and comparability across specifications.

Table 1: Monetary policy rate benchmark

Period	Benchmark / Instrument	Definition / Notes
Through Dec. 31, 2016	LEBAC (35-day)	35-day LEBAC interest rate.
Jan. 2, 2017–Aug. 7, 2018	7-day repo corridor (pases) midpoint	Midpoint of the 7-day repo (pases) rate corridor.
Aug. 8, 2018–Jan. 20, 2020	LELIQ	LELIQ rate designated as the monetary policy reference.
Jan. 21, 2020–Jan. 5, 2022	LELIQ (shortest maturity, W.A. of last awarded auction)	Weighted-average rate of the shortest-maturity LELIQ auctioned in the most recent awarded tender; effective until the next auction.
Jan. 6, 2022–Dec. 17, 2023	28-day LELIQ (announced)	BCRA-announced policy rate for the 28-day LELIQ.
Dec. 18, 2023–Jul. 21, 2024	Overnight reverse repo	1-day passive repo (pase pasivo a un día) rate.
Jul. 22, 2024–Jul. 10, 2025	LEFI	Rate announced by the BCRA and accrued by the Fiscal Liquidity Bills (LEFI).
From Jul. 11, 2025 onward	—	The BCRA stopped announcing a monetary policy rate.

Notes. LEBAC = Central Bank bills; LELIQ = Liquidity bills; LEFI = Fiscal Liquidity Bills. Source: Informe Monetario Diario (BCRA).

3.2 Monetary Policy Shocks

For Argentina, shocks are usually defined by isolating *sharp* (i) changes in the monetary policy rate, (ii) currency depreciation episodes, (iii) changes in monetary aggregates, and (iv) fiscal consolidations/expansions. Given data limitations, specifically the lack of forecasts for monetary aggregates and the yearly frequency used in the government's budget balance private estimates, I focus on (i) only.

Inspired by Romer and Romer (2004), Ramey (2016) and Baioni (2024), I treat shocks as the innovations from a Taylor-style rule that captures the systematic component of rate setting. These residuals, $\hat{\varepsilon}_t$, are used in the Local Projections stage with HAC inference.

The Taylor rule specification (1) is a parsimonious version of Neder and Farías (2019) that incorporates inflation expectations (assuming a forward-looking, rational consolidated government). The policy rate enters as $\ln i_t$, and the baseline policy-rule regressors are the policy rate lagged one period ($\ln i_{t-1}$), twelve-month-ahead REM inflation expectations ($\mathbb{E}_t\pi_{t+12}$), output growth measured by the *Estimador Mensual de Actividad Económica* (EMAE), Δy_t with $y_t \equiv \ln(\text{EMAE}_t)$, the FX market gap ($FX_t$), and an inflation-targeting indicator (IT_t). Series are aligned in levels, applying seasonality pre-treatment where relevant. In robustness checks, I also consider the real exchange rate ($REER_t$), current monthly inflation (π_t), and twenty-four-month expectations ($\mathbb{E}_t\pi_{t+24}$), all with similar outcomes.

$$\ln i_t = \alpha + \rho \ln i_{t-1} + \beta_\pi \mathbb{E}_t\pi_{t+12} + \beta_y \Delta y_t + \beta_{fx} FX_t + \delta IT_t + \varepsilon_t. \tag{1}$$

Table 2 reports a dynamic Taylor-type rule in which a large and highly significant lag of the policy rate ("policy smoothing") accounts for most of the monthly variation in $\ln i_t$. Because the dependent variable is itself persistent, the specification delivers a mechanically high R^2 even when contemporaneous fundamentals contribute little information at the monthly frequency.

Crucially, a high R^2 in a dynamic rule is not problematic for our objective—constructing exogenous shocks as residuals. What matters is that the regression captures the systematic component of policy (the predictable responses and inertia), leaving residuals that are orthogonal to included information. Serial correlation and heteroskedasticity in those residuals are addressed downstream by (a) using HAC standard errors in the Local Projections and (b) including lags of the shock, so inference remains valid. In short, the high R^2 reflects the well-known persistence of policy rates, not overfitting; it helps purge the systematic part and improves the quality of the shock series.

Beyond dynamics, the FX gap enters with a positive and statistically significant coefficient, indicating tighter policy when the exchange-market premium widens. By contrast, twelve-month-ahead expected inflation and real-activity growth are not significant at conventional levels, and the inflation-targeting indicator primarily captures a level shift with only marginal incremental explanatory power. Overall, the rule reacts more to currency-market stress than to near-term expectations or activity.

Table 2: Baseline Taylor Rule Regression (Argentina, monthly)

		$\ln i_t$	
Symbol	**Variable**	**Coef.**	**(SE)**
$\ln i_{t-1}$	Lagged policy rate (log)	0.980^{***}	(0.049)
$\mathbb{E}_t\pi_{t+12}$	Expected inflation, 12 mo. ahead (REM)	−0.0003	(0.0438)
Δy_t	Output growth (EMAE, monthly $\Delta \ln$)	−0.256	(0.385)
FX_t	FX market gap (parallel–official premium)	0.082^{**}	(0.0355)
IT_t	Inflation-targeting dummy	0.064^{*}	(0.0345)
α	Constant	0.025	(0.180)
Observations		108	
R^2		0.9525	
Adj. R^2		0.9502	
$F(5, 102)$		409.26	
Root MSE		0.099	

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Definitions: $y_t \equiv \ln(\text{EMAE}_t)$ so Δy_t is monthly activity growth; expectations from the BCRA *REM*.

Table 3 indicates that expected inflation Granger-causes the policy rate, while the reverse is weak at best; jointly, $\{\mathbb{E}_t\pi_{t+12},\ FX_t,\ IT_t\}$ help forecast $\ln i_t$. This is precisely what I want the first stage to capture: systematic responses of policy to available information. By absorbing that predictability in-sample, the residuals I take as monetary policy shocks are closer to the unpredictable component required for the LP impulse-response analysis.

Regression diagnostics also suggest: (i) *Serial correlation in residuals.* Breusch–Godfrey tests at lags 1–2 reject white noise. Raw residuals are thus *predictable to some degree* and

Table 3: Granger-Causality Tests (VAR, lags 1–4)

Dependent var.	Excluded (cause)	Test	Stat. (χ^2)	p-value
$\ln i_t$	$\mathbb{E}_t\pi_{t+12}$	Pairwise	19.03	0.001
$\ln i_t$	FX_t	Pairwise	7.73	0.102
$\ln i_t$	IT_t	Pairwise	5.72	0.221
$\ln i_t$	All three jointly $\{\mathbb{E}_t\pi_{t+12},\ FX_t,\ IT_t\}$	Block	32.14	0.001
$\mathbb{E}_t\pi_{t+12}$	$\ln i_t$	Pairwise	9.08	0.059

Notes: Pairwise rows test whether the excluded variable Granger-causes the dependent variable. "Block" tests the joint null that $\{\mathbb{E}_t\pi_{t+12},\ FX_t,\ IT_t\}$ do not Granger-cause $\ln i_t$.

cannot be treated as i.i.d. shocks at the IRF stage.[4] (ii) *Heteroskedasticity.* Breusch-Pagan/Chow-White tests indicate non-constant variance; standard errors must be robust. (iii) *Collinearity.* Variance Inflation Factors (VIFs) are moderate overall (mean ≈ 3.3) and higher for inertia and expectations (around 5). This helps explain why the expectations slope becomes imprecise once lagged $\ln i_t$ is included; I keep expectations on theoretical grounds to avoid contaminating shocks with systematic responses. Taken together, these results support the chosen information-set controls as plausible systematic drivers. Figure 1 reports the corresponding residuals $\hat{\varepsilon}_t$, used as monetary policy shocks.

Defining shocks as the unexplained component of policy after controlling for systematic reactions is standard in the residual and narrative traditions. Although autocorrelation and heteroskedasticity may affect the efficiency of coefficient estimates, they do not compromise the validity of using residuals to identify monetary policy shocks. As in Romer and Romer (2004), shocks are defined as the unexplained component of policy actions after controlling for systematic responses, and remain valid as long as the specification isolates the unsystematic part of policy. Robust inference methods, such as Newey and West (1987) corrections or including lags of the shock in Local Projections (Ramey, 2016), addresses these issues without undermining identification.

Argentina experienced repeated regime shifts over the sample. I keep a parsimonious baseline and retain the full sample but remain break-aware in interpretation. The timeline below (Table 4) highlights salient episodes that are captured by the constructed series.

[4] This is common in monthly rules with smoothing; see Jordà (2005) and surveys such as Ramey (2016).

Figure 1: Estimated monetary policy shocks $\hat{\varepsilon}_t$.

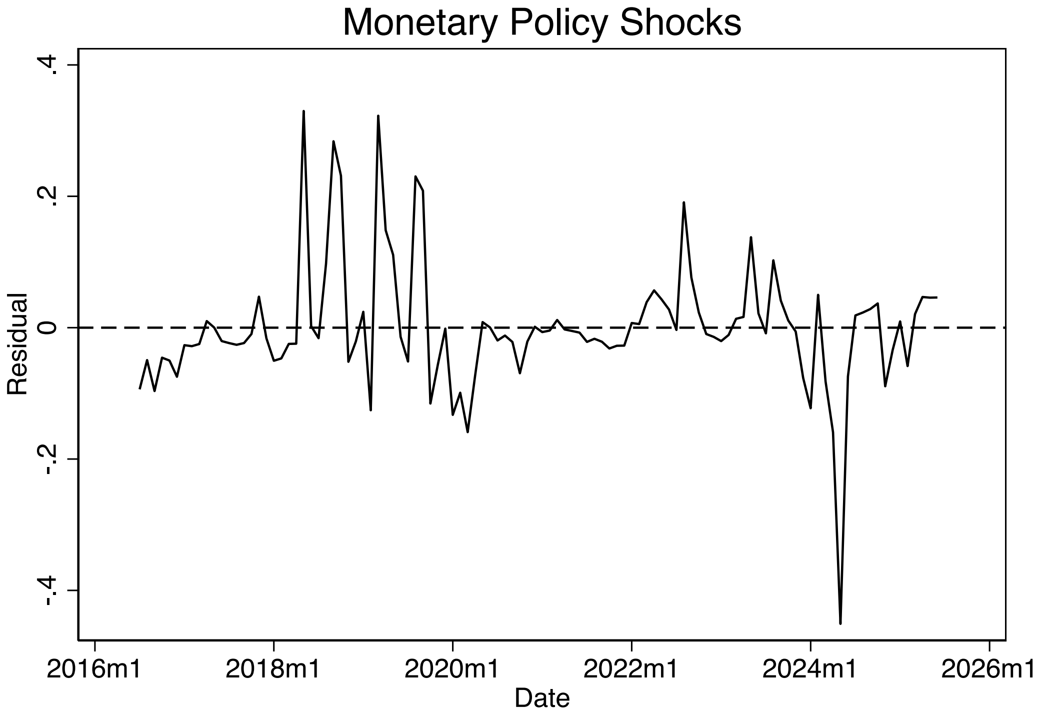


Table 4: Notable monetary and FX events in Argentina, 2016–2025

Date	Event	Notes
Jun 2016	Inflation-targeting setup	Start of IT regime
Oct 2018	Tightening under IMF program	Base targeting; very high rates
Aug 2019	PASO shock and FX controls	Sudden depreciation; controls reinstated
Mar 2020	COVID response	Liquidity expansion and rate cuts
Oct 2022	Crawling-peg dynamics	Greater FX management
Dec 2023	Early Milei adjustment	Fiscal consolidation and monetary shift

3.3 Local Projections for IRFs

Following Jordà (2005), instead of estimating a full VAR and then reading off impulse responses, LPs estimate—*for each horizon h*—a separate linear regression where the dependent variable is the future outcome and the regressor of interest is today's shock. The coefficient on today's shock at horizon h is the impulse response at h.

For each horizon $h = 0, \dots, 48$ and for each inflation component $i \in \mathcal{I}$, let L denote the lag operator ($L^s x_t = x_{t-s}$). I estimate

$$\pi^i_{t+h} = \alpha^i_h + \sum_{s=0}^{3} \beta^i_{h,s}\, L^s(\varepsilon^{\mathrm{mp}}_t) + \sum_{s=1}^{2} \rho^i_{h,s}\, L^s(\pi^i_t) + \sum_{s=1}^{2} \gamma^i_{h,s}\, L^s(\Delta y_t) + \sum_{s=1}^{2} \delta^i_{h,s}\, L^s(f_t) + \kappa^i_h\, CC_t + \iota^i_h\, IT_t + u^i_{t+h}. \tag{2}$$

Notes. π^i_t is inflation for CPI component i (Headline, Tradables & Non-tradables, and the 9 COICOP subindices); $\varepsilon^{\mathrm{mp}}_t$ is the monetary-policy shock using the Taylor-rule residual based approach; $y_t \equiv \ln(\mathrm{EMAE}_t)$; f_t is the fiscal deficit as % of GDP; CC_t is the capital-controls dummy; IT_t is the inflation-targeting dummy. Exchange-rate variables (e.g., REER, FX gap) and sovereign risk (EMBI–Argentina) are excluded from the control set at this point to avoid conditioning on key transmission channels of monetary policy.

The monetary-policy shock enters contemporaneously and up to three lags ($s = 0, \dots, 3$), while all other regressors enter with two lags only ($s = 1, 2$). The control set includes $\Delta y_t \equiv \Delta \ln(\mathrm{EMAE}_t)$ and f_t; in addition, the capital-controls indicator CC_t and the inflation-targeting indicator IT_t enter contemporaneously as regime dummies.

If the shock $\varepsilon^{\mathrm{mp}}_t$ is (conditionally) exogenous given lags of the system and controls, then

$$\beta^i_{h,0} \approx \frac{\partial}{\partial \varepsilon^{\mathrm{mp}}_t} \mathbb{E}\Big[\pi^i_{t+h} \,\Big|\, \mathcal{F}_{t-1}\Big],$$

i.e., the IRF of inflation component i at horizon h. $\mathcal{F}_{t-1}$ denotes the information available at time $t-1$ (lags of the outcome and controls, plus any predetermined regime indicators).

Because the dependent variable overlaps across time (e.g., π_{t+h} and π_{t+h+1} share realizations), errors are serially correlated up to order h. Therefore, Newey–West (HAC) standard errors with bandwidth $h+1$ are used for each h, reporting 68% and 90% normal-approximation confidence bands. The shock is rescaled to a 10% policy-rate increase for easier interpretation. For comparability, responses and bands are normalized to zero at $h = 0$. In addition and for robustness checks, I report wild-bootstrap (boottest) confidence intervals—999 replications per horizon and per series, at the 68% and 90% levels (seed = 2025) in Appendix B.

4 Results

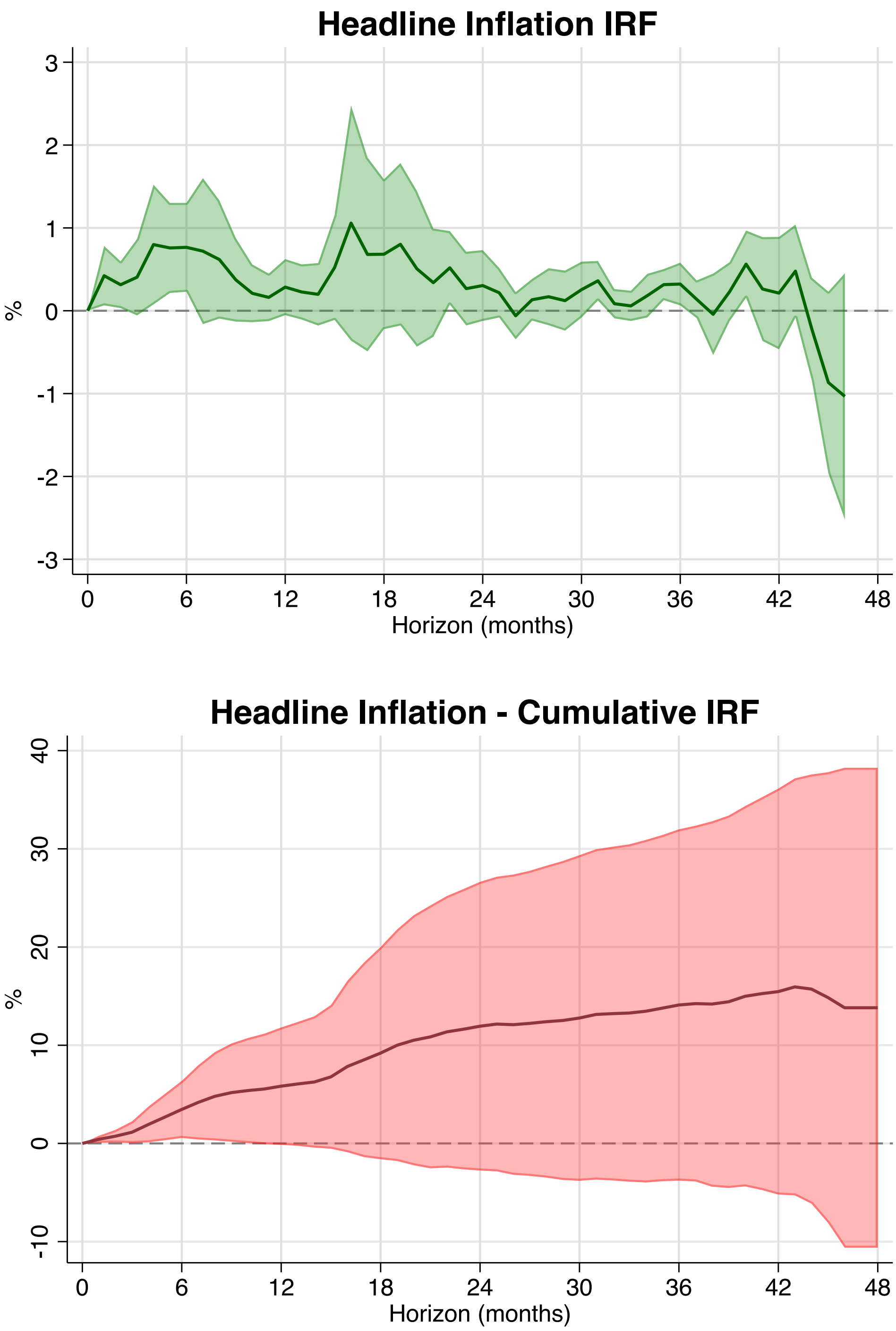
4.1 Aggregate CPI IRFs

4.1.1 Headline CPI IRF

Following a 10% policy-rate hike, the point estimate for headline inflation moves above zero within a few months, reaches a hump between roughly one and one-and-a-half years, and then drifts back toward zero at longer horizons. This pattern suggests a short-run "price-puzzle"–type response—consistent with policy reacting to incipient inflationary pressures or with indexation channels that delay pass-through of tighter monetary conditions to prices. Any point estimate above zero should be interpreted as the inflation rate on that horizon being higher than the one had the shock not occurred. As an example, 16 months after the shock, the monthly inflation rate is 1 percentage point higher than the no-shock inflation rate.

The cumulative IRF rises steadily for the first two to three years, reflecting the positive short to medium-run monthly responses, and then tends to flatten with very wide confidence intervals toward the sample's end. Economically, the cumulative path implies that a contractionary shock does not produce immediate disinflation; instead, inflation accumulates above the no-shock path for a prolonged period before the effect dissipates. Given the breadth of the long-horizon intervals, however, inference beyond about two years should be made cautiously:

Figure 2: IRFs to a 10% policy rate hike: Headline Inflation.



Notes. IRFs estimated with Local Projections using my own estimates of monetary policy shocks from Taylor-rule residuals. Shock is normalized to a 1000 basis point (10%) increase in the monetary policy rate. The solid line shows the point estimate; the shaded regions are 90% confidence intervals based on Newey–West HAC standard errors. A value of 1 at horizon h means inflation is 1 p.p. higher than the no-shock path at that horizon in response to a +10% policy-rate shock.

while the point estimate remains positive, the uncertainty bands encompass much smaller or even opposite outcomes.

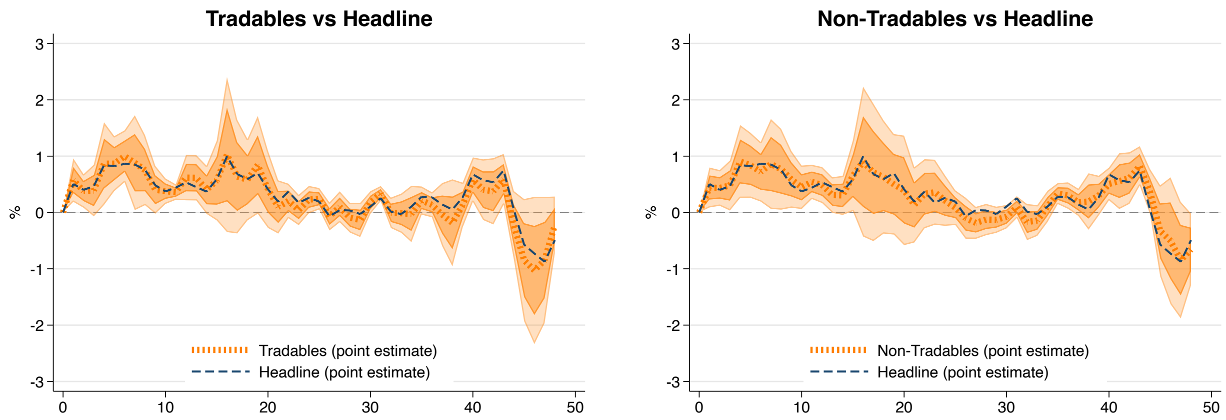
Note that non-cumulative LP bands need not widen monotonically with the horizon: each h is estimated in a separate regression with HAC errors, so widths reflect horizon-specific sampling variation (effective sample size, $\mathrm{Var}(\pi_{t+h} \mid \mathcal{F}_{t-1})$, and regressor design/collinearity), not a mechanically accumulating forecast error. By contrast, cumulative responses aggregate estimation error across horizons, so their bands typically widen with h (cross-horizon covariances are usually positive).

4.1.2 Tradables & Non-tradables CPI IRFs

I built the T/NT aggregates from the CPI categories using the Economic Commission for Latin America and the Caribbean's (ECLAC) conservative COICOP rule of thumb: goods-dominant groups are *Tradables* and services-dominant groups are *Non-tradables*. In our mapping, *Food & Beverages*, *Clothing & Footwear*, and *Household Equipment & Maintenance* are in T; *Housing & Utilities*, *Health*, *Transport*, *Communications*, *Education*, *Recreation/Culture*, *Restaurants & Hotels*, and *Miscellaneous* are in NT. For mixed cases (e.g., *Transport*), I classify by the group's dominant nature rather than item-by-item, to keep the series stable and comparable. During the national CPI intervention period, I applied the same mapping to the CPI of San Luis so the T/NT split remains consistent over time.

The Tradables overlay indicates a faster and larger disinflationary response to a +10% policy-rate shock than headline. The Tradables point estimate drops below zero earlier and by a greater magnitude, while the Headline line remains closer to zero over the same horizons. Consistent with this, the orange 68% and 90% bands tend to sit farther below zero for Tradables in the early-to-mid horizons, suggesting a meaningfully stronger (though not definitive) response. By later horizons, both series drift back toward zero, consistent with a largely *temporary* effect. Overall, the evidence points to *earlier and sharper inflation pass-through* to tradable prices.

Figure 3: IRFs to a 10% policy rate hike: Tradables & Non-tradables



Horizon (months) Horizon (months)

Notes. IRFs estimated with Local Projections using monetary policy shocks from Taylor-rule residuals. The shock is normalized to a 1000 bp (10%) policy-rate increase. The *solid orange* line is the point estimate for the series shown in each panel; the *orange shaded* regions depict 90% and 68% HAC (Newey–West) confidence bands. The *dashed* line shows the point-estimate IRF for headline inflation (contrasting color). The vertical axis is in percentage points of the monthly inflation rate (fixed y-scale $\pm 3\%$ in both panels). A value of -0.30 at horizon h means inflation is 0.30 p.p. lower than the no-shock path at that horizon in response to a $+10\%$ policy-rate shock.

For Non-tradables, the response is more muted and delayed. The Non-tradables point estimate generally moves less than in Tradables and often tracks the Headline line, with wider overlap of the confidence bands and the zero line—so the case for a distinct Non-tradables response is weaker. This pattern is in line with the idea that exchange-rate and import-price channels drive the initial disinflation in Tradables, while stickier contracts, local-cost shares, and administered components dampen and delay adjustment in Non-tradables. Overall, an ordering by magnitude emerges as $|\Delta \text{ Tradables}| > |\Delta \text{ Headline}| > |\Delta \text{ Non-tradables}|$. These are *preliminary* impressions given the band overlap, and they should be read alongside sample windows and specification checks.

Because INDEC does not publish separate tradables/non-tradables indices, a second-best approach aggregates COICOP groups into T/NT buckets. This choice warrants caution in interpretation. Many groups bundle both tradable and non-tradable items, and some items' tradability evolves over time; time-varying CPI weights and basket rebasings further shift exposure to exchange-rate and tariff shocks. Administered prices, regulated tariffs, and price-control episodes are disproportionately concentrated in non-tradables, potentially biasing pass-through comparisons relative to tradables. Future work should construct these indices using finer levels of disaggregation.

4.2 Disaggregated CPI IRFs

4.2.1 Monthly Inflation Rate IRFs

When initially calculating the IRFs for each component of the CPI, I observed a similar pattern across all components, with differences arising mainly in terms of sharpness and variance. This suggests a common underlying dynamic affecting all prices, consistent with inertial components. These results are shown in Figure 4.

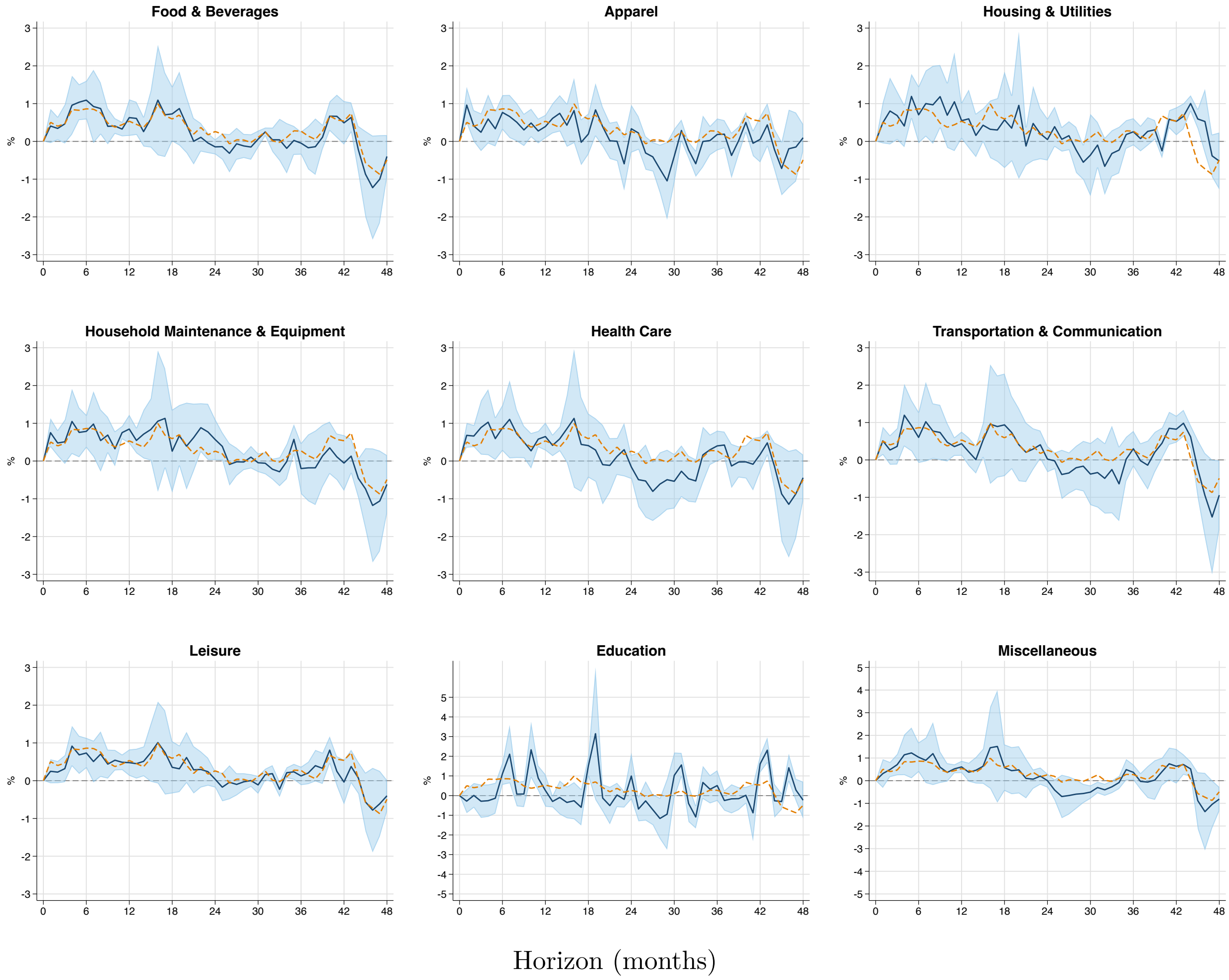
Two visual checks help anchor interpretation. First, the dashed headline series typically sits inside the component bands and close to the component's point estimate, which is a simple diagnostic given that headline is a weighted aggregate. Second, responses are pinned to zero at $h = 0$ by construction, so the absence of an immediate "impact" in the figure should not be read as evidence against immediate effects[5].

All categories from the disaggregated IRFs except Education share a clear two-phase dynamic: a short-run increase in monthly inflation over roughly the first year after the shock, followed by a gradual sign reversal with point estimates turning negative between $h \approx 18$ and $h \approx 30$ and drifting further below zero toward the end of the horizon. The *Headline Inflation* response (dashed) lies near the cross-sectional average—mildly positive at short horizons and negative later. Heterogeneity aligns with economic structure: *Tradables* tend to cross zero earlier and fall more sharply, whereas more service-heavy items (e.g., regulated or contract-heavy components) adjust later and more smoothly; *Education* and *Miscellaneous* exhibit the greatest volatility. Taken together, the pattern is consistent with strong short-run cost/FX

[5]Shocks in reality occur at different times during each month, and when aggregating those impacts on a monthly basis I might not capture that feature. Therefore, for easier comparison between components, I assume shocks do not impact prices contemporaneously.

pass-through and indexation that delay disinflation, followed by the aggregate-demand channel asserting itself once contracts reset and real activity slows.

Figure 4: IRFs to a 10% policy rate hike: Nine Disaggregated Components



Notes. IRFs estimated with Local Projections using my own estimates of monetary policy shocks from Taylor-rule residuals. Shock is normalized to a 1000 basis point (10%) increase in the monetary policy rate. The solid line shows the point estimate; the light blue shaded region is 90% confidence interval based on Newey–West HAC standard errors. The orange dashed line shows the point estimate IRF for headline inflation. The vertical axis is in percentage points of the monthly inflation rate. Interpretation: a value of -0.30 at horizon h means inflation is 0.30 p.p. lower than the no–shock path at that horizon in response to a +10% policy–rate shock.

A simple clustering emerges. Goods-intensive categories (*Tradables*, *Food & Beverages*, *Apparel*) show earlier peaks and earlier zero crossings, consistent with faster pass-through and inventory re-pricing. Service- or policy-heavy items (*Housing & Utilities*, *Education*, *Miscellaneous*) move more slowly and with larger, lumpier swings, which fits tariff/tuition calendars and contract indexation. *Transportation & Communications* displays a mid-horizon hump above zero that is larger than most categories, suggestive of energy and regulated-fee channels.

Interestingly, following a monetary policy contraction, there is a notable tendency for prices to rise for nearly two years. This pattern prompts a critical reflection on whether the observed effects might actually be indicative of monetary expansions rather than contractions. The delayed response and subsequent rise in prices suggest that the initial tightening might not be effectively curbing inflation but rather acting as a sterilization practice to moderate the effects of a significant monetary expansion. This raises questions about the true nature of the monetary policy stance during these periods.

After this initial phase, the IRFs indicate a decline in prices, often falling below the threshold of zero around the two-year mark. This could imply that the monetary policy contraction eventually becomes effective in lowering prices. This nuanced pattern suggests a complex interplay between monetary policy actions and inflation dynamics, emphasizing the need for a deeper examination of the transmission mechanisms. Overall, these findings challenge the conventional interpretation of monetary policy contractions, warranting further investigation into the potential underlying monetary expansions that might be driving these trends.

Amplitude and precision differ systematically. Mid-horizon bands narrow for several goods categories—indicating relatively informative estimates—while bands widen at the longest horizons for most panels, reflecting shrinking effective samples and accumulated uncertainty. I therefore place more weight on features up to roughly $h \in [6, 30]$ and treat end-point movements with caution.

There is mild asymmetry in many series: the early positive hump is typically sharper than the late negative response. That pattern is consistent with sticky prices, partial indexation and credit cost pass-through followed by a slower demand-driven disinflation as contracts renew. Where the late undershoot dips below zero and then reverts, I interpret it as transitory overshooting rather than sustained deflation pressure.

The clearest, sharper responses are seen in *Apparel* (early, well-defined dip followed by rebound), *Housing & Utilities* (pronounced initial drop and gradual return), and *Transportation*

& Communications (noticeable mid-horizon hump above zero). *Miscellaneous* shows a mild positive drift for much of the horizon and a late downturn. Small near-zero oscillations appear in *Food & Beverages*, *Household Equipment & Maintenance*, and *Leisure*; *Health Care* moves gently with low precision. In terms of variance, *Education* has the widest bands and the noisiest path overall.

I report in Table 5 some summary metrics by component for the monthly inflation IRFs: (i) the first zero hit, (ii) the peak (max) monthly response and its timing, (iii) the minimum (most negative) response and its timing, (iv) the first horizon at which the 90% band excludes zero, (v) the share of periods in which the 90% band excludes zero and (vi) the number of sign changes in each series. These compactly capture the "long and variable lags" across categories.

Zero hit reports the first month when the *inflation* IRF's point estimate crosses zero; for Headline, Tradables, and Non-tradables this occurs around 25–26 months, indicating that monthly inflation typically stays above its no–shock path for roughly two years before reverting. Peak point responses are modest for most groups (max $\Delta\pi$ near 1–1.5 pp), with a clear outlier in *Education* (3.15 pp at $h = 19$). Minimum point responses are small and occur late (e.g., *Transportation & Communications* -1.53 pp at $h = 47$), consistent with gradual normalization.

Earliest statistical significance arrives quickly (month 1 for the three aggregated components, months 1–3 for most series, at 4 for *Leisure*, and at 6 for *Education*). The share of significant horizons is 40% for Headline, 31% for Tradables, and 42% for Non-tradables—suggesting slightly more persistent statistical evidence on the non–tradable side. The *Sign changes* metric reveals varied oscillatory behavior: it is pronounced in *Education* (20 flips) and *Apparel* (14), versus much smoother profiles in *Non-tradables*, *Transportation & Communications*, and *Miscellaneous* (5 each).

Table 5: Stylized facts from monthly inflation IRFs

	Monthly inflation IRF (pp, mo)					**Significance/shape**		
Component	Zero hit	Max $\Delta\pi$	at h	Min $\Delta\pi$	at h	Earliest 90%	Share 90% (%)	Sign changes
Headline Inflation	26	1.00	16	-0.87	47	1	40	7
Tradables	26	1.03	16	-1.03	46	1	31	9
Non-tradables	25	0.90	4	-0.85	47	1	42	5
Food & Beverages	23	1.09	6	-1.23	46	2	29	7
Apparel	17	0.96	1	-1.05	29	1	33	14
Housing & Utilities	21	1.19	5	-0.66	32	3	27	7
Household Equipment & Maintenance	26	1.13	17	-1.18	46	1	35	9
Health Care	20	1.13	16	-1.15	46	1	33	7
Transportation & Communications	24	1.20	4	-1.53	47	1	29	5
Leisure	24	1.01	16	-0.78	46	4	31	9
Education	2	3.15	19	-1.16	28	6	25	20
Miscellaneous	24	1.51	17	-1.37	46	2	35	5

Notes. Monthly inflation IRF (pp, mo) reports the point response of inflation ($\Delta\pi$) and timing (months). *Zero hit*: first horizon when the estimate crosses zero. *Max/Min* $\Delta\pi$: largest positive/negative point responses and their horizons. **Significance/shape**: *Earliest 90%*: first significant month. *Share 90%*: proportion of horizons with significance. *Sign changes*: number of sign flips.

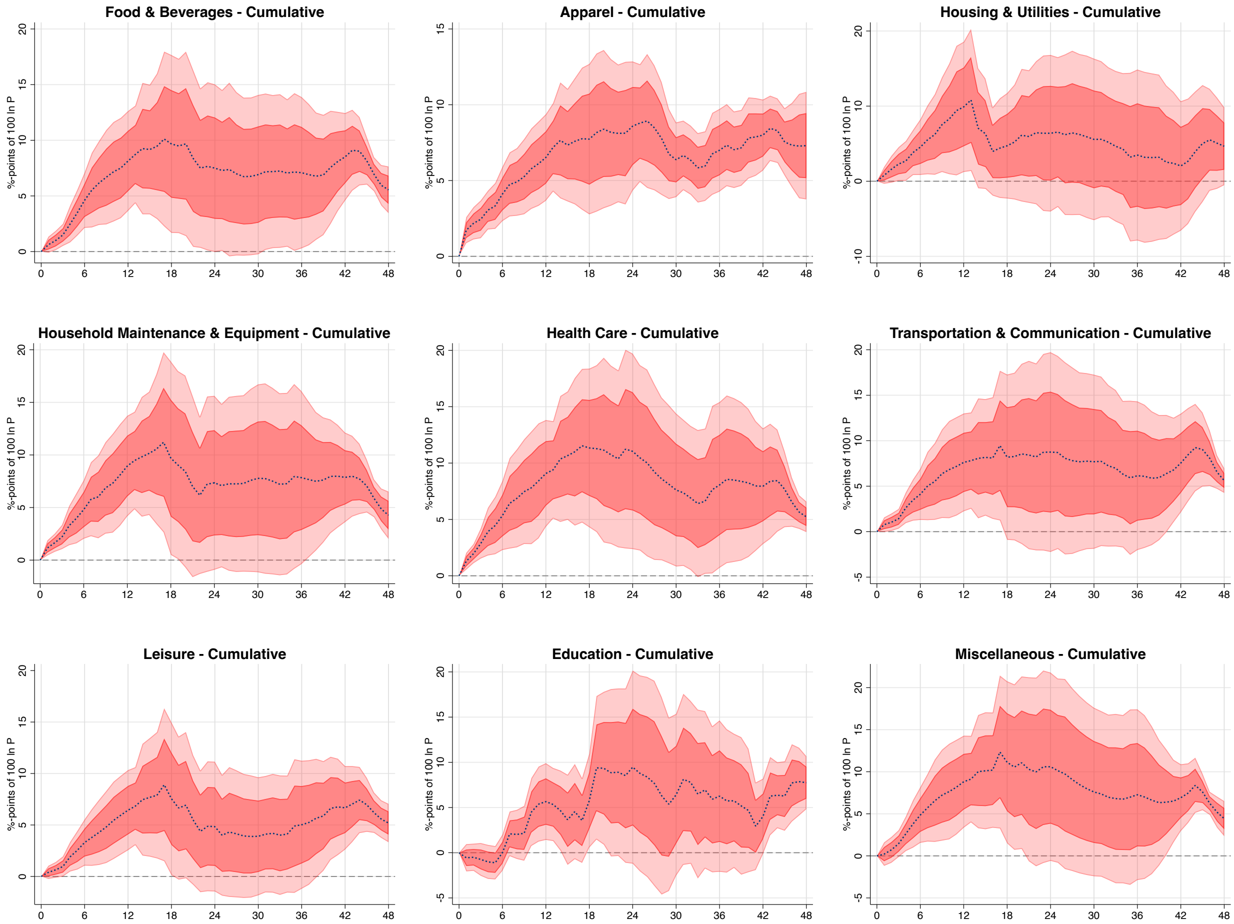
4.2.2 Cumulative Inflation (Price Level) IRFs

Cumulative responses[6] show that the short-run inflation hump translates into a sizeable price-level build-up across most categories: accumulated effects rise steeply through year 1, peak between $h \approx 12$ and $h \approx 24$, and then erode only gradually as monthly inflation turns negative relative to the no-shock situation. By $h = 48$, the net cumulative effect remains above zero for all components. This is mirrored in Table 6, where *Cum12* and *Cum24* are strongly positive everywhere and *Cum36* and *Cum48* indicates only partial reversal. Overall, a contractionary policy shock eventually lowers monthly inflation, but within my sample window it does not deliver a net decline in the price level, underscoring long and variable lags with sectoral adjustment.

Uncertainty also behaves differently in levels than in monthly rates. Because the cumulative IRF is a running sum, estimation noise aggregates mechanically across horizons; this produces widening bands even when the underlying monthly responses are stable. In my robustness overlays (HAC versus wild bootstrap), the bands largely overlap.

[6] *Construction note:* I set the horizon-0 response to zero for comparability and compute the cumulative IRF for component i as $C_h^i = \sum_{j=0}^{h} \widehat{\beta}_{j,0}^{i}$, where $\widehat{\beta}_{j,0}^{i}$ is the coefficient on the contemporaneous shock in the horizon-j local-projection. Bands use Newey–West HAC standard errors; robustness uses equal-tailed wild-bootstrap bands with 999 replications (seed 2025).

Figure 5: Cumulative IRFs to a 10% policy rate hike: Nine Disaggregated Components



Horizon (months)

Notes. IRFs estimated with Local Projections using my own estimates of monetary policy shocks from Taylor-rule residuals. Shock is normalized to a 1000 basis point (10%) increase in the monetary policy rate. The solid line shows the point estimate; the light blue shaded region is 90% confidence interval based on Newey–West HAC standard errors. The orange dashed line shows the point estimate IRF for headline inflation. The vertical axis is in cumulative percentage points (sum of monthly deviations from the no–shock path). Interpretation: a value of -0.50 at horizon h means cumulative inflation up to h is 0.50 p.p. lower than the no–shock path in response to a +10% policy–rate shock.

Two cautions are in order. Effective sample size shrinks with the horizon, so endpoint estimates rely on fewer observations and are more sensitive to outliers or regime breaks (e.g., FX control episodes, COVID-era policies, the 2023–24 adjustment). In addition, the cumulative IRF traces the effect of a *one-time* shock; it should not be read as the long-run consequence of a sustained tightening.

Policy-wise, these patterns are consistent with "long and variable lags." A contractionary innovation eventually lowers monthly inflation, but the cumulative price level remains above the no-shock path for years in several categories. This suggests that one-off rate moves are unlikely to deliver level reversals on their own; the speed of disinflation hinges on expectations management, the pace of relative-price realignments (regulated prices), and the credibility of the regime.

When calculating the cumulative effect of the shock, the outcomes differed significantly yet with a strong inertial component in price variations. This could imply that the monetary policy rate might not fully capture the effect of monetary policy in Argentina, and that the money supply could be a better measure, despite its estimation challenges.

Table 6 summarizes cumulative price–level effects (*Cum12*, *Cum24*, *Cum36*, *Cum48*) in response to a +10% policy–rate shock[7]. Level effects for the three aggregated components are sizeable and persistent. *Headline Inflation* peaks at 9.12 pp at $h = 17$ and reverses by 61.9% by $h = 48$, leaving 5.65 pp as the net effect after four years. *Tradables* peak a bit higher at 9.73 pp (also $h = 17$), reverse by 64.3%, and stand at 6.26 pp at four years. *Non-tradables* peak at 8.72 pp ($h = 17$), reverse by 60.6%, and settle at 5.28 pp at $h = 48$.

Cross–sectional patterns at standard horizons help interpret persistence. At one year, the largest cumulative effects are in *Housing & Utilities* (9.89 pp), *Health Care* (9.08 pp), and *Household Equipment & Maintenance* (8.94 pp), with *Education* the smallest (5.66 pp). By two years, the ranking reshuffles: *Health Care* (11.04 pp), *Miscellaneous* (10.60 pp), and

[7] Coefficients are percentage points (pp) of $100 \ln P$. For example, $\mathrm{Cum}_{12} = 7.61$ for *Headline inflation* implies that one year after the shock the CPI level is about 7.61 pp higher—roughly a 7.9% increase ($e^{0.0761} - 1$).

Education (9.47 pp) are now top; Headline and Non-tradables are among the lowest (4.54 and 4.42 pp). By four years, *Education* (7.74 pp) and *Apparel* (7.30 pp) remain elevated, while *Household Equipment & Maintenance* and *Miscellaneous* have fallen back (4.26 and 4.42 pp).

The *Cumulative peaks* block reports each series' maximum price–level effect and its timing (often $h = 17$), together with *Rev.@48 (%)*—the share of that peak unwound by month 48. Reversal is very large for *Apparel* and *Education* (both $\approx$ 82%), moderate for the aggregates ($\sim$ 60%), and relatively small for *Miscellaneous* (35.8%) and *Household Equipment & Maintenance* (38.0%). The highest cumulative peak overall is *Miscellaneous* (12.35 pp at $h = 17$), followed by *Health Care* (11.54 pp), *Household Equipment & Maintenance* (11.21 pp), and an earlier–peaking *Housing & Utilities* (10.82 pp at $h = 13$).

Table 6: Cumulative price-level effects (pp of $100 \ln P$)

	Cumulative (pp of $100 \ln P$)				**Cumulative peaks**		
Component	Cum12	Cum24	Cum36	Cum48	Peak cum.	at h	Rev.@48 (%)
Headline Inflation	7.61	4.54	5.37	5.65	9.12	17	61.91
Tradables	7.83	6.76	7.45	6.26	9.73	17	64.34
Non-tradables	7.74	4.42	4.25	5.28	8.72	17	60.57
Food & Beverages	8.14	7.50	7.09	5.55	10.11	17	54.83
Apparel	6.52	8.60	7.00	7.30	8.93	26	81.77
Housing & Utilities	9.89	6.39	3.49	4.66	10.82	13	43.06
Household Equipment & Maintenance	8.94	7.35	7.84	4.26	11.21	17	38.03
Health Care	9.08	11.04	8.06	5.23	11.54	17	45.32
Transportation & Communications	7.62	8.75	6.15	5.61	9.46	17	59.26
Leisure	6.44	4.84	5.02	5.19	8.91	17	58.21
Education	5.66	9.47	6.26	7.74	9.47	24	81.78
Miscellaneous	8.81	10.60	7.27	4.42	12.35	17	35.82

Notes. Cumulative (pp of $100 \ln P$): running sum of monthly inflation responses at $h = 12, 24, 36, 48$. Units: percentage points of the price level ($100 \cdot \ln P$). **Cumulative peaks**: *Peak cum.* = maximum cumulative effect and its horizon; *Rev.@48* = share of the peak unwound by $h = 48$.

Overall, the evidence points to broad–based medium–run upward pressure on the price level that peaks after roughly a year and a half and partially unwinds thereafter.

5 Conclusions

Argentina's monetary policy exhibits long and variable lags, and the variability is largely explained by heterogeneous transmission across goods and services with very different pricing regimes and exposures.

From cumulative impulse responses, a +10% policy-rate shock raises the price level with statistically detectable effects over many horizons. All CPI components show sizeable, persistent level effects: peaks around 9–12 pp at $h \approx 17$ and partial reversals of about 40%–80% by $h = 48$. At standard horizons, cumulative effects remain positive—about 5–10 pp at one year, 5–11 pp at two years, and 3.5–8 pp at three years—while monthly inflation typically stays above its no-shock path for 20–26 months.

Timing and shape metrics are modest in point terms (max $\Delta\pi \approx$ 1–1.5 pp), with *Education* an outlier (3.15 pp at $h = 19$); minima tend to be small and late (e.g., *Transportation & Communications* -1.53 pp at $h = 47$). Non-Tradables peak early in point responses (0.90 pp at $h = 4$), whereas tradable-intensive groups build a later hump; sign flips are frequent in *Education* and *Apparel* but much smoother in *Non-tradables*, *Transportation & Communications*, and *Miscellaneous*. Earliest 90% significance occurs within months 1–6.

Cross-sectionally, housing- and health-related groups dominate at one year; by two years, *Health Care* and *Miscellaneous* are most elevated; by four years, *Education* and *Apparel* remain high. Peak levels are largest in *Miscellaneous* (~ 12.35 pp), and reversal by $h = 48$ ranges widely (from $\sim 36\%$ to $\sim 82\%$).

While a rate hike typically signals tightening (Baioni, 2024), the estimates challenge the textbook prediction of immediate disinflation. The policy rate has not always been the operative anchor; shifting regimes make rate movements an imperfect proxy for stance (Mishkin, 1999). Policy should allow for peaks near $h \approx 17$ and zero-hit around two years, prioritize a clearly communicated operative instrument (including aggregates when relevant), manage expectations, and use disaggregated indices to tailor complementary tools.

In this sense, it is up for discussion whether Argentina's Central Bank raising its monetary policy rates has been a case of contractionary monetary policy or if it responded solely to a sterilization mechanism compensating for massive monetary expansions in a fiscal dominance regime, which would in turn be expansionary policy.

Argentina seems to experience a version of the impossibility trilemma: if the government wants to keep the exchange rate fixed or stable along with a budget deficit that requires monetary financing or debt, the Central Bank must set its administered rates to absorb the money overhang. Therefore, the monetary policy rate is not a target but a result of the consolidated government's behavior.

Policy implications follow. Peaks around $h \approx 17$ and zero–hit near two years counsel patience: premature reversals risk entrenching inflation when cumulative effects are still building. When the rate is not the operative instrument, targeting monetary aggregates (or an augmented monetary base including interest–bearing liabilities) can offer clearer implementation and communication. Managing expectations is essential in the presence of inertia and indexation. Finally, monitoring disaggregated indices helps tailor complementary tools: price–administered sectors, highly traded goods, and services with contractual rigidities react on different clocks, with markedly different peak sizes (e.g., 12.35 vs. 8.72 pp) and reversal profiles ($\sim 36\%$ vs. $\sim 82\%$).

Future work could extend this framework to the study of exchange rate shocks and to more granular levels of price disaggregation, where sectoral rigidities may amplify asymmetries and improve Tradables and Non-tradables classification. Another promising direction is to combine local projections with machine learning and large language models, using economic news or central bank communication to construct text-based measures of policy stance and expectations.

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A Data sources, definitions, and periods

Table 7: Variable definitions: symbols and construction

Variable	Symbol	Construction / Transform
Policy rate	i_t	Various policy rates, monthly;
Inflation (headline)	π_t	Monthly CPI inflation.
CPI components[a]	π_t^i	Monthly inflation by COICOP groups (disaggregated series).
Output (activity)	y_t	$y_t \equiv \ln(\text{EMAE}_t)$; Δy_t is monthly growth.
Inflation expectations (12m)	$\mathbb{E}_t\pi_{t+12}$	REM twelve-month-ahead CPI; last vintage before month-end.
FX market gap	FX_t	Parallel–official exchange-rate premium (ratio minus 1).
Inflation-targeting dummy	IT_t	Regime indicator equal to 1 during IT episodes.
Capital-controls dummy	CC_t	Regime indicator equal to 1 when FX controls are in place.
Sovereign risk	$EMBI_t$	JPM EMBI–Argentina, monthly.
Real effective exchange rate	$REER_t$	Log real multilateral effective exchange rate.

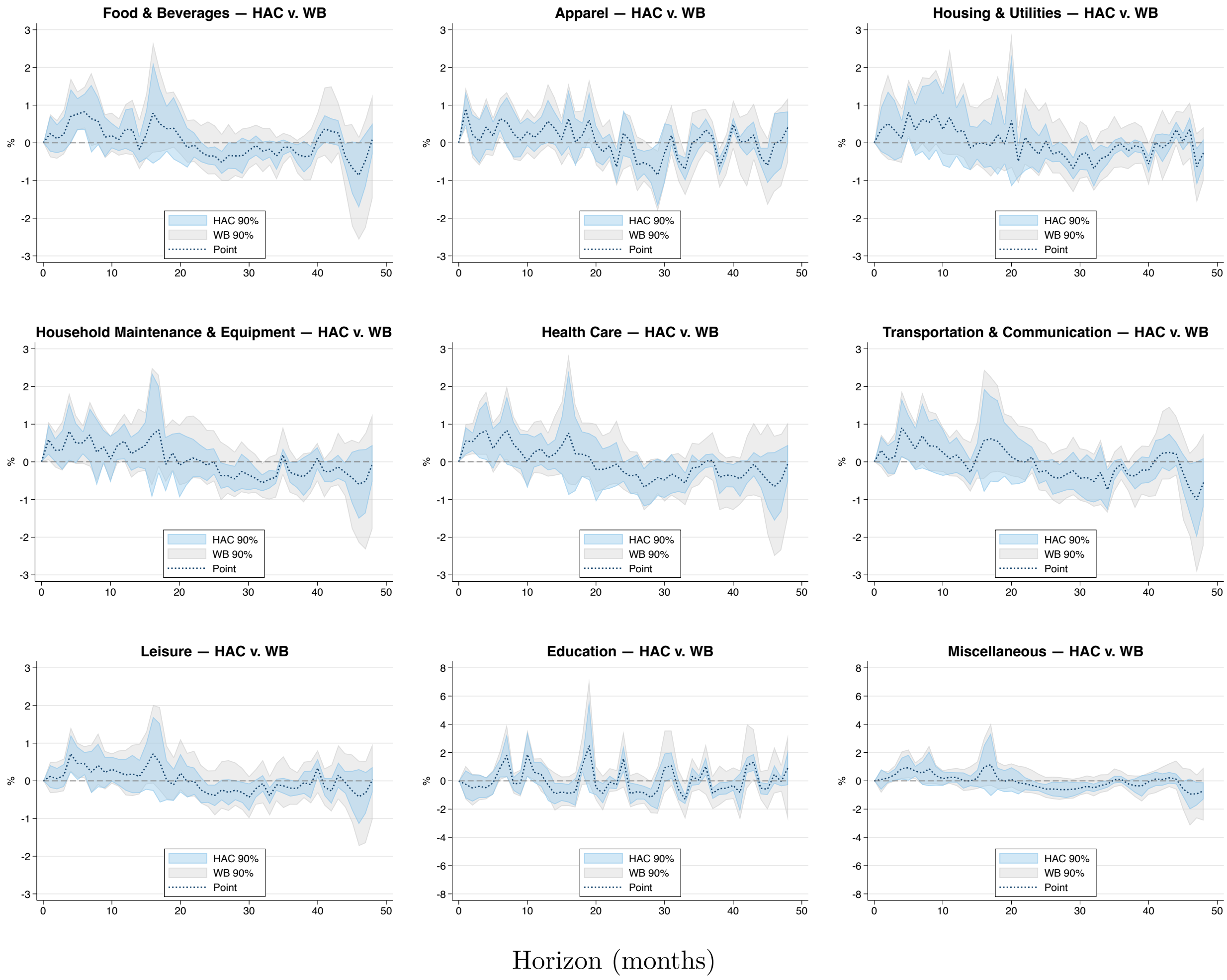
Table 8: Data sources and sample periods

Variable	Symbol	Source	Period
Policy rate	i_t	BCRA	2016m6–2025m6
Inflation (headline)	π_t	INDEC / DEC San Luis[a]	2016m6–2025m6
CPI components	π_t^i	INDEC / DEC San Luis[a]	2016m6–2025m6
Output (activity)	y_t	INDEC (EMAE)	2016m6–2025m6
Inflation expectations (12m)	$\mathbb{E}_t\pi_{t+12}$	BCRA–REM	2016m6–2025m6
FX market gap	FX_t	BCRA / Ámbito Financiero	2016m6–2025m6
Inflation-targeting dummy	IT_t	Author's coding	2016m6–2025m6
Capital-controls dummy	CC_t	Author's coding	2016m6–2025m6
Sovereign risk	$EMBI_t$	J.P. Morgan (EMBI)	2016m6–2025m6
Real effective exchange rate	$REER_t$	BCRA	2016m6–2025m6

Notes. [a] During the national CPI interruption, CPI subcomponents are backfilled using DEC San Luis and re-aggregated. **Sources.** INDEC CPI and EMAE (Instituto Nacional de Estadística y Censos (INDEC), 2025b,a); San Luis CPI (Subsecretaría de Programación Macroeconómica (SSPM), 2025); BCRA ITCM/ITCRM (REER) and REM (Banco Central de la República Argentina (BCRA), 2025b,a).

B Robustness Checks: Wild Bootstrap

Figure 6: IRFs to a 10% policy-rate hike: HAC v. WB (90% bands) 9 disaggregated components



Notes. Local-Projection IRFs to a shock normalized to a 1,000 bps (10%) policy-rate increase. Solid line: point estimate. Light blue shading: 90% HAC (Newey–West) band. Gray shading: 90% wild-bootstrap band (999 reps, seed 2025). Dashed horizontal line at zero. Vertical axis in percentage points of the monthly inflation rate.