

Anchored or Adrift? A Note on Measuring Inflation Expectations Anchoring*

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Abstract

We develop a behavioral model of inflation which contains an indicator that quantifies the expectations unanchoring risk over the business cycle. We estimate this model using US and Canadian inflation and output gap data. We find that during the post-pandemic inflation surge, the macroeconomic data are compatible with non mean-reverting expectations, which reveals an elevated, albeit transitory, risk of expectations drifting away from the target. This risk has fully subsided in Canada but has not yet entirely dissipated in the United States. We find no evidence of such risk on the downside, despite prevailing policy narratives in the 2010s decade. (100 words)

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1 Introduction

In the post-COVID-19 area, inflation surged well above its two percent target and reached levels not experienced in decades across most major economies. Such an inflation surge raised policy concerns that inflation expectations could become unanchored, which would amplify the surge and complicate the stabilization task of central banks.¹ How to identify, quantify and monitor such a risk to inform monetary policy? In this paper, we combine macroeconomic data with a model-based analysis to gauge this unanchoring risk by tracking the degree of mean-reversion in expectations in the US and in Canada over 1991-2025.

In our framework, agents can switch between up to two forecasting models of inflation. Both belief-types co-exist and their relative prevalence evolves over time as a function of their recent relative forecast accuracy. We embed this behavioral model of inflation expectation formation into a standard New Keynesian Phillips curve and take it to the data using non-linear least squares.

The estimates identify two statistically distinct belief-types: a mean-reverting and a trend-chasing model. Mean-reverting forecasts converge back to the target. By contrast, trend-chasers extrapolate recent inflation forward, so that their beliefs drift away from the target in the wake of transitory exogenous inflationary shocks, which poses an unanchoring risk. Since the composition of aggregate expectations varies along the business cycle, it gives rise to a state-dependent unanchoring risk. The key outcome of our exercise is a time series of the estimated expectation unanchoring indicator with an associated (theory-driven) unanchoring threshold, which provides a straightforward and contemporaneous gauge of the risk of expectations drifting away from the target.

We find that such risk is asymmetric and prevails only when inflation overshoots the

¹For instance, Fed Chairman Powell and Bank of Canada's Governor Macklem both underscored this concern in 2023 [[Powell, 2023](#); [Macklem, 2023](#)].

target, much less so on the downside, when inflation undershoots, for instance during the decade following the Great Financial Crisis (GFC) or the onset of the COVID-19 pandemic. Our estimates do not confirm any risk of expectations unanchoring in the pre-COVID-19 period, neither in the US – despite nominal rates at the effective lower bound (ELB) – nor in Canada, where below-target inflation had also sparked such concerns. However, deviations of realized inflation from the target were smaller during the below-target episode prior to the pandemic than during the inflation surge that followed, which might also contribute to the observed asymmetry.

We then highlight how the risk of expectations unanchoring materialized between 2021Q3 and 2022Q3 in both countries amid the post-pandemic inflation surge but dissipated in the wake of the ensuing disinflation. Interestingly, such risk dissolved (much) more quickly in Canada than in the US, where the unanchoring indicator displays overall more persistence and has remained elevated. Furthermore, we show how the inflation expectations dynamics implied by our simple estimated framework – that only requires macroeconomic data – neatly maps onto movements in real-world expectations, while avoiding the caveats associated with the use of expectation data in estimation exercises (see, e.g., [Ozden 2025](#) for a discussion).

Our parsimonious approach to heterogeneity and autoregressive formulation broadly connect to the literature on the modeling of expectations under uncertainty about fundamental shocks; see, e.g., [Andrade et al. \[2022\]](#); [Okuda et al. \[2025\]](#). In particular, we relate to the empirical literature on heterogeneous inflation expectations; see [Branch \[2004\]](#) for early empirical evidence, [D’Acunto et al. \[2023\]](#) for a recent review and, e.g, [Meeks and Monti \[2023\]](#) on their quantitative relevance in accounting for inflation dynamics. We model heterogeneous expectation with an heuristics-switching model, introduced in the seminal application of the replicator dynamics in [Brock and Hommes \[1997\]](#), which has sparked a lengthy literature on both the theoretical and empirical fronts; see [Hommes](#)

[2021] for a review.² Our state-dependent anchoring view echoes [Gürkaynak et al. \[2007\]](#) and [Gáti \[2023\]](#).

Closest to our work [Cornea-Madeira et al. \[2019\]](#); [Cornea-Madeira and Madeira \[2022\]](#) and [Bolt et al. \[2019\]](#) document evidence of switching in forecasting beliefs in, respectively, inflation and housing prices. Mirroring our measure of expectations anchoring, [Bolt et al. \[2019\]](#) link the relative prevalence of trend-chasing behaviors to bubble risk in the housing market. We extend [Cornea-Madeira et al. \[2019\]](#); [Cornea-Madeira and Madeira \[2022\]](#) by estimating the belief-types from the macroeconomic data, emphasizing the role of recent inflation history, and a policy application to two countries. The comparison of Canada and the United States contrasts an inflation-targeting small open economy with a large economy under an explicit dual mandate. The Federal Reserve further announced an average-inflation-targeting framework in August 2020, while the Bank of Canada emphasized flexible inflation targeting in its policy renewal in 2021. Cross-country evidence could reveal how these differences may affect the unanchoring risk, especially in the post-pandemic inflation surge.

2 Dynamic heterogeneity in inflation expectations

2.1 A model of expectation formation with time-varying heterogeneity

The model encompasses J agent-types, indexed by j , that differ only by their inflation forecasting model. Each type j forecasts inflation using an AR(1) model:

$$E_{j,t}^* \pi_{t+1} = \phi_j \pi_{t-1}, \tag{1}$$

²This literature is also related to the equally lengthy literature on fundamentalists-versus-chartists models in behavioral finance developed in the wake of [Frankel and Froot \[1986\]](#).

where the * superscript indicates that expectations need not be rational, inflation π is expressed in deviation from its target, the latest observation is in $t-1$, and the autoregressive parameter $\phi_j \in \mathbb{R}$ is the only cross-type difference. An AR(1) specification offers parsimony while remaining general enough to describe vastly different expectation dynamics [see, *inter alia*, [Hommes et al., 2023](#)].³

Two-type specification We use $J = 2$ agent-types, which is sufficient to allow for the co-existence of polar effects of expectations on inflation, namely in the case of a mean-reverting and a trend-chasing type. When fundamental shocks drive inflation away from the target, a mean-reverting model would pull expectations back toward it and constitute a tailwind for monetary policy. By contrast, a trend-chasing model would extrapolate the current inflation gap into the future, posing an expectations unanchoring risk and, therefore, would represent a headwind for monetary policy.

Aggregation The two views about future inflation co-exist in the economy. In each period t , a fraction $\mathbf{n}_{1,t}$ of the agents use the type-1 model and the other $\mathbf{n}_{2,t} \equiv (1 - \mathbf{n}_{1,t})$ the type-2 model. Aggregate inflation expectations are the weighted average of the two:

$$E_t^* \pi_{t+1} = \mathbf{n}_{1,t} \phi_1 \pi_{t-1} + \mathbf{n}_{2,t} \phi_2 \pi_{t-1}. \quad (2)$$

Time-varying forecast heterogeneity Agents switch between the two forecasting models according to their relative forecasting accuracy over the recent periods. We use the

³In detail, steady-state beliefs correspond to $\phi_j = 0$, random-walk beliefs or naive expectations to $\phi_j = 1$, $\phi_j < 0$ describe so-called contrarian beliefs, $\phi_j > 0$ maps onto adaptive or mean-reverting expectations (with $0 \leq \phi_j < 1$) or trend-chasing beliefs ($\phi_j > 1$).

following form of the replicator dynamics to specify how the shares $n_{1,t}$ and $n_{2,t}$ evolve:

$$U_{j,t} = -\frac{FE_t^j}{FE_t^1 + FE_t^2}, \quad (3)$$

$$FE_t^j = \sum_{k=0}^{K-1} |E_{j,t-k-2}^* \pi_{t-k-1} - \pi_{t-k-1}|, \quad (4)$$

$$n_{j,t} = \delta n_{j,t-1} + (1 - \delta) \frac{\exp(\beta U_{j,t})}{\exp(\beta U_{1,t}) + \exp(\beta U_{2,t})}, \quad (5)$$

which we now unpack step-by-step. Variable $U_{j,t}$ gauges type j 's accuracy: per Eq.(3), it declines with the size of the absolute forecast errors,⁴ denoted by FE^j and defined in Eq. (4), which are the errors that would have resulted had type j been used to forecast inflation over the last K periods. Such a finite horizon allows for structural breaks and captures bounded memory documented in survey [Malmendier and Nagel, 2016] and lab data [Anufriev and Hommes, 2012]. Eq. (5) is the replicator dynamics, through which the forecasting model that delivers smaller errors gains traction at the expense of the other. The speed at which agents switch to the better-performing model is determined by $\beta > 0$, where higher values mean a faster switch.⁵ Finally, parameter $\delta \in [0, 1)$ introduces inertia: only a fraction $1 - \delta$ of agents considers switching types in each period. We interpret larger δ values as reflecting greater inattention to newly observed data.

In our model, forecasts are meant to be those of private agents (firms and households) typically underlying the New Keynesian frameworks. On the empirical front, survey evidence shows that households and firms' inflation expectations share many character-

⁴Absolute errors are convenient in environments where forecast errors are fat-tailed amid occasionally large shocks since the linear penalty prevents a few extreme episodes from disproportionately driving switching dynamics. For this reason, a performance based on absolute values is commonly used in the related literature [Cornea-Madeira et al., 2019; Cornea-Madeira and Madeira, 2022]. By contrast, squared errors would be excessively sensitive to large errors, which might lead to numerical overflows in the exponential term of the switching algorithm. Conversely, a performance measure based on a log function might become insensitive to these large shocks since values would flatten out quickly as errors increase.

⁵Parameter β is sometimes referred to as the intensity of choice or the degree of rationality of the agents when using the heuristic-switching model defined by Eqs. (3)-(5); see, for instance, Anufriev and Hommes [2012]. $\beta = 0$ fixes both types at $n_{j,t} = 1/2$, independently of their relative forecasting performances, while $\beta \rightarrow \infty$ makes all agents instantly adopt the better rule. For this reason, the limiting case $\beta \rightarrow \infty$ has been called the "neoclassical limit."

istics and tend to be backward-looking [see, e.g., [Weber et al., 2022](#); [Andrade et al., 2022](#); [D’Acunto et al., 2023](#); [D’Acunto and Weber, 2024](#); [Okuda et al., 2025](#)]. The heuristic-switching structure can be motivated by laboratory evidence in forecasting experiments documenting that subjects rely on simple backward-looking forecasting rules; see, e.g., [Hommes \[2021\]](#) for a review. [Cornand and Hubert \[2020\]](#) also document the external validity of experimental forecasts by showing that they are comparable to those from survey data. Note also that our modeling approach allows for policy-variant expectations since monetary policy affects the composition of expectations *via* changes in inflation and, hence, the relative performances of each forecasting type.

Our expectation model, albeit simple, can account for key qualitative implications of important behavioral theories and empirical observations. If the data are consistent with an extrapolative type, an AR(1) process provides a parsimonious representation of the overreaction behavior underlying diagnostic expectations, where agents overweight recent shocks [see for instance, [Bordalo et al., 2018, 2022](#)]. In our model, trend-extrapolating expectations would amplify both upward (positive) and downward (negative) inflation since the autoregressive coefficient is applied to the inflation gap (realized inflation relative to the target). Our model also incorporates sluggishness in the belief updating in line with sticky information, noisy information, or rational inattention models that all lead to the prediction that average expectations adjust gradually and with traction on past forecasts; see, e.g., the review in [Coibion et al. \[2018\]](#).

2.2 Embedding heterogeneous expectations in an inflation model

To bring the above expectation model to the data, it remains to be specified how inflation expectations relate to inflation. We use a standard New Keynesian Phillips curve (NKPC)

with behavioral expectations in line with the literature surveyed earlier:

$$\pi_t = \gamma E_t^* \pi_{t+1} + \kappa y_t + \xi_t, \quad (6)$$

where $\gamma \in (0, 1)$ is the discount factor, y_t summarizes the state of aggregate demand, and $\kappa > 0$ is the slope resulting from nominal rigidity. Several micro-foundations support the aggregation of the economy-wide inflation expectation $E_t^* \pi_{t+1}$ using Eq. (2), and provide a corresponding interpretation of the shock ξ .⁶ Following the related literature (see, e.g. [Cornea-Madeira et al. 2019](#)), we treat this shock as a residual in the estimation of Eq. (6) in Section 2.4.

Within the context of this model, we envision inflation as fluctuating around a stable long-run anchor (namely, its target) due to persistent but transitory shocks, summarized in y and ξ . This interpretation aligns with our post inflation-targeting sample and the rejection of the unit root in our time series; see Section 2.3.⁷ Additionally, within the context of the NKPC, both forecasting models (1) are mis-specified since agents misperceive inflation as being driven by past inflation values instead of past output gaps. Such misperception finds support in New Keynesian lab experiments where subjects typically overlook the effect of output gap when forecasting inflation [[Assenza et al., 2021](#)]. Note also that our switching model between two belief-types boils down to a time-varying AR(1) process for inflation expectations. Against this background, our model can be framed in terms of behavioral learning equilibria (BLE), in which agents' expectations match the mean and first-order autocorrelation of realized inflation [[Hommes and Zhu, 2014](#); [Hommes et al.,](#)

⁶One example is the diverse-belief approach of [Kurz et al. \[2013\]](#) where the shock ξ_t then represents the average forecast across all firm-types of their relative prices, which need not be zero (in log-deviation) in the presence of heterogeneous and boundedly rational expectations. Another example is developed in [Arifovic et al. \[2025\]](#) where the only requirement is a discrete and finite distribution of agent-types, and the shock ξ retains the usual interpretation of a cost-push shock. See also, for example, [Andrade et al. \[2019\]](#) for yet another alternative.

⁷Note that under rational expectations, assuming that y follows a stationary AR(1) process with an autoregressive parameter $\rho_y \in (0, 1)$, in line with the rejection of the unit root reported in Appendix Table A2, the model is determinate since $\gamma < 1$.

2023]. We discuss our results through the lens of this framework in Section 3.1.

Measuring expectation anchoring In each period, the average autoregressive coefficient in aggregate expectations provides a simple and intuitive measure of the degree of anchoring of inflation expectations. This indicator, denoted by ρ_t , is computed as the weighted average of the two estimated autoregressive coefficients, using the time-varying share of each forecaster type:

$$\rho_t \equiv \phi_1 \mathbf{n}_{1,t} + \phi_2 (1 - \mathbf{n}_{1,t}) \in [\phi_1, \phi_2]. \quad (7)$$

An increase in ρ_t weakens mean-reversion in the aggregate inflation expectations and jeopardizes their anchoring. The target even becomes expectationally unstable – in other words, average expectations do not converge back to it following transitory shocks and lose their anchoring – whenever $\rho_t \geq \frac{1}{\gamma}$, where the anchoring threshold $\bar{\rho} \equiv \frac{1}{\gamma} > 1$.⁸ Moreover, even if $\rho_t < \bar{\rho}$, the closer it is to the threshold, the more likely escape dynamics can drive inflation away from the target under (at least partly) backward-looking expectations (see, for example, Branch and Evans 2011).

While this indicator is derived from the dynamics of short-run expectations, increasing values of ρ_t (even below $\bar{\rho}$) imply that shocks have a longer-lasting effect on expectations, and it will take more time for these expectations to revert to the target. Extrapolating short-term forecasts in our model into a few periods in the future may then proxy for longer-run anchoring, which is typically the measure of expectations anchoring in CBs [Williams, 2022], consistent with the well-documented agents' finite planning hori-

⁸To see this, insert aggregate expectations (2) into the inflation equation (6), which results in a backward-looking process where inflation in t depends on inflation in $t - 1$. Under such process, inflation is expectationally stable when the (absolute) value of the first derivative with respect to π_{t-1} is strictly lower than one, which is the case whenever $\gamma(\phi_1 \mathbf{n}_{1,t} + \phi_2 (1 - \mathbf{n}_{1,t})) \equiv \gamma \rho_t < 1$, or $\rho_t < \frac{1}{\gamma} \equiv \bar{\rho}$. Since γ is a discount factor, $\bar{\rho}$ is just above one. Note that if the common knowledge assumption is relaxed, the discount factor in the NKPC can be lower than γ [Rognlie, 2019]. In such case, the threshold $\bar{\rho} =$ can be interpreted as a conservative measure of the unanchoring risk.

zons [Coibion et al., 2023; Gust et al., 2026]. Survey evidence also indicates positive co-movements, and even strong correlations, between short-horizon and longer-horizon expectations; see, e.g., Candia et al. [2024].

2.3 Macroeconomic data

Data sources To estimate the model, we need inflation and aggregate demand data. US's prices data are obtained from the US Bureau of Labor Statistics's monthly Consumer Price Index (CPI), from which we compute the year-over-year inflation rate. While annualized month-over-month inflation might better align with the one-step-ahead expectations in the NKPC, it is strongly driven by short-lived movements in the prices of several highly volatile CPI components such as food or energy; see Appendix Figure A1. By contrast, the year-over-year inflation rate tends to smooth out such idiosyncracies and is therefore considered the main indicator of the build-up of inflationary pressures by policy makers. The inflation targeting mandate of the Bank of Canada is set in terms of year-over-year total CPI inflation, monetary policy is also described as such in the US, and CBs refer to this measure in their communication with the public.⁹

We use two indicators of aggregate demand. The first one is unemployment, measured as the difference between the US' monthly unemployment rate – obtained from the US Bureau of Labor Statistics's Employment Situation release – and its 10-year rolling average. The second one is output gap, computed as the difference between the real Gross Domestic Product (GDP) – from the US Bureau of Economic Analysis – and the real potential GDP – from US Congressional Budget Office – available at a quarterly frequency.

These datasets are retrieved from the FRED database from the Federal Reserve Bank of

⁹Our results are nevertheless robust to using the annualized seasonally-adjusted month-over-month CPI inflation (see Appendix Table A1 for the estimation outcome, and Appendix Figure A2 for the dynamics of the anchoring indicator). On a technical note, the residuals autocorrelation stemming from the mechanical overlapping periods in the monthly year-over-year time series is mild in our baseline specification (see Appendix Figure A3). Appendix Table A3 further shows that our results are robust to a GMM/IV approach where we use additional lags as instruments.

St. Louis and cover 1991M3 to 2025M4.

For Canada, prices data are obtained from the monthly Statistics Canada's all-items CPI (CANSIM 18-10-0004-01), with inflation measured as the year-over-year CPI growth. Canada's monthly unemployment data is retrieved from the Labour Force Survey (CANSIM 14-10-0287-01), also detrended by its historical 10-year average. As for the output gap, we use the quarterly estimates of the Bank of Canada's Staff Economic Projections [see [Champagne et al., 2018](#)]. The data also covers 1991M3 to 2025M4. All macroeconomic series used in the estimations are the latest (final) data.

Data description Figure 1 presents the dynamics of monthly inflation (plain thick lines) and the output gap (dashed lines) in each country over the sample. Both the US and Canada target a two-percent inflation (dashed orange horizontal line). The Fed formally established such an explicit target in 2012, but had settled "behind-the-scene" on it already in the 1990s [[Wells, 2024](#)]. The Bank of Canada adopted an explicit inflation target of two percent already in 1991. Appendix Table A2 shows that the unit root is rejected in all the time series.¹⁰

The overall inflation outlook of the US and Canada in the past 10 years is similar, which both countries featuring stable inflation that hovers slightly below the two-percent target until the COVID-pandemic in 2020. Thereafter, a short-lived dip further below target in the wake of the early lockdown measures is followed by a significant surge that propels inflation to roughly 8 percent in both economies during 2021-2023, before cooling down but remaining above target. The dynamics of the output gap is also broadly similar across the two countries, to the exception of the years following the GFC which appears to have had a deeper and longer negative impact on the volatility of the economy in the US than in Canada. Most recently, the paths of the output gap also diverge along the disinflation

¹⁰When modeling US quarterly inflation as a trend-cycle model over 1970–2004, [Stock and Watson \[2007\]](#) find that the data fail to reject the unit root, but the 1984–2004 "moderation" sample features a substantially lower variance of the permanent trend component compared to 1970–1983.

from the 2022 inflation peak, with positive values in the US and negative ones in Canada.

2.4 Estimation strategy

The model consists of the expectation formation mechanism given by Eqs. (1) to (5), along with the inflation model given by the NKPC in Eq. (6). We denote by $\theta = (\phi_1, \phi_2, \beta, \delta, \kappa)'$, the vector of parameters to estimate, and we calibrate K and γ . Following [Cornea-Madeira et al. \[2019\]](#), we set $K = 4$ quarters or $K = 12$ months and as usual in the business cycle literature, we calibrate $\gamma = 0.996$.¹¹ Let us write the residual as $\xi_t(\theta) = \pi_t - \hat{\pi}_t(\theta)$, where π_t is the observed inflation gap from the data and $\hat{\pi}_t(\theta)$ is the predicted inflation gap using the model, the measure of aggregate demand, and a given parameter set θ . Parameters are estimated using non-linear least squares (NLS) with the objective function $\hat{\theta} \in \arg \min_{\theta} \sum_{t=1}^T \xi_t(\theta)^2$, where our data sample size consists of T observations and we use the NL2SOL algorithm [[Dennis Jr et al., 1981](#)]. Parameter restrictions are $(\phi_1, \phi_2, \beta, \kappa) \in \mathbb{R}^4$ and $0 \leq \delta \leq 1$. For convenience, we let $\phi_2 \equiv \phi_1 + \Delta\phi$ and estimate $\Delta\phi$.¹² In line with the related literature aforementioned, we use agnostic initial conditions and set $n_{1,0} = n_{2,0} = 50\%$. We use heteroskedasticity and autocorrelation consistent (HAC) standard errors via the Bartlett kernel with a truncation of 24 lags.¹³

Therefore, we do not impose any constraint on the values of the autoregressive parameters ϕ_1 and ϕ_2 , nor do we impose that they differ from each other. We instead let the data speak: Do the estimated values fit the aforementioned behavioral interpretation?

¹¹Our results are robust to alternative values of the discount factor γ and the memory window K ; see Appendix Tables [A4](#) and [A5](#), respectively.

¹²This inequality is only an ordering normalization used to resolve the permutation (label-switching) indeterminacy of the two types in finite-mixture models. It does not restrict ϕ_1 or ϕ_2 because any solution with $\Delta\phi < 0$ can be relabeled (by swapping the type indices) to produce an observationally equivalent likelihood. This normalization improves numerical stability and prevents type jumping across samples or rolling windows, without loss of generality [e.g., [Frühwirth-Schnatter, 2006](#)].

¹³This choice is in line with the related literature, e.g. [Cornea-Madeira and Madeira \[2022\]](#). Appendix Table [A6](#) shows that our results are robust to using alternative standard-error corrections, namely the White's heteroskedasticity-consistent standard errors (HCCME), the prewhitened-HAC standard errors (which improves finite-sample inference by filtering first the residuals to remove short-run autocorrelation before applying the HAC correction), and HAC standard errors using a truncation of 12 lags.

3 Dynamics of expectation anchoring in the US and in Canada

3.1 Estimation results

Table 1 presents the outcomes of the estimation across different specifications for the US (columns I to V) and Canada (columns VI to X). Columns (I) and (VI) report the baseline model for the US and Canada, respectively. Columns (II) tests the robustness of the other estimates to the absence of inertia in the evolution of belief-types by imposing $\delta = 0$ in Eq. (5). Columns (III) and (VIII), and (IV) and (IX), restrict the sample to, respectively, the period following the onset of the COVID-19 pandemic, starting in April 2020, and the period following the GFC, starting in January 2007. Columns (V) and (X) report the estimates using the output gap, only available at a quarterly frequency in both countries.

Parameter ϕ_1 is estimated to be positive and significantly below one for both countries and across columns, which aligns with mean-reverting inflation beliefs, whereas positive and statistically significant estimates of $\Delta\phi$ indicate $\phi_2 > \phi_1$, which is consistent with the co-existence of two beliefs under our parsimonious two-type specification. Moreover, in almost all datasets, ϕ_2 is significantly greater than one, particularly at quarterly frequency (Cols. V and X), which suggests that the macroeconomic data in both countries are compatible with the presence of trend-chasing beliefs. In the subsequent analysis, we refer to the first type of agents as mean-reverters, and the second type as trend-chasers.

Turning to the intensity of choice β , significantly positive estimates across all columns reflect agents' rationality in adjusting their forecasting model in response to errors in favor of the better performing model. As for the degree of inattention δ , we are unable to find evidence of inattention in US data given the near zero estimation of δ . In Canada, δ is estimated around 0.57, suggesting a review of forecasting strategies on average every two periods (months). Finally, the estimated NKPC slope κ has the expected sign: it is negative when using the unemployment gap and positive when using the output gap.

Overall, the macroeconomic data do not reject the behavioral model and the dynamics of both US and Canadian inflation are consistent with significant time-varying heterogeneity in inflation expectations.

3.2 Dynamics of expectation anchoring in the US and Canada

Figure 2a reports the three-month moving average time series of the expectation anchoring indicator ρ_t for the US (orange line) and Canada (blue line), with 95% confidence intervals, along with the stability threshold $\bar{\rho}$, and the recessionary episodes in each country (vertical shaded areas). Figure 2b zooms in over the last 10 years for increased readability.

On average over the sample, the aggregate anchoring indicator is rather high in both countries: it is on average 0.94 (with a 0.036 standard error) for the US and 0.88 (with a 0.032 standard error) for Canada. Through the lens of the BLE framework, [Hommes and Zhu \[2014\]](#) show that within an NKPC model with AR(1) inflation beliefs, there can be a unique stable low-persistence equilibrium, a unique high persistence one, or three equilibria where the low and the high-persistence ones are stable, and the medium-persistence one is not. In any of these equilibria, by definition, the persistence in the inflation expectations, measured in our framework by ρ_t , matches the realized persistence in inflation. Within the context of our model, our estimates are consistent with the existence of either multiple equilibria where the high-persistence one is locally stable, or a single stable high-persistence equilibrium.¹⁴

Turning to the dynamics of the anchoring indicator, it is overall more volatile in the US than in Canada due to the absence of significant inertia in the US data (see, again, Col. I of Table 1). However, before 2020, its dynamics is broadly similar in the two countries. It mostly remains well below the threshold, especially in Canada, with occasional spikes

¹⁴We cannot pin down the exact numerical values of our parameters that delimit these two cases since they depend on model parameters specific to the framework of [Hommes and Zhu \[2014\]](#).

towards or beyond it, in particular in the US in the wake of the GFC. Overall, this pattern in both countries indicates that the macroeconomic data before 2020 are compatible with mean-reverting and, hence, well-anchored inflation expectations, and an absence of expectation unanchoring risk. Interestingly, this is true even during the 2010 decade dominated by concerns about below-target inflation amid interest rates at the effective lower bound in the US. This is an important insight given the emphasis during the 2010s decade on the risk of expectation unanchoring on the downside, i.e. below target; see, *inter alia*, [Draghi \[2014\]](#); [Ehrmann \[2015\]](#); [Dudley \[2016\]](#). Our model does not support such concerns, in either of the two countries.

By contrast, the most dramatic rise in the unanchoring indicator happens during the post-pandemic inflation surge when it well exceeds the anchoring threshold. Over this episode, the aggregate data clearly indicate a rejection of mean-reversion in expectations in favor of extrapolation of the rising inflation trend into the future. This translates into a heightened unanchoring risk, which could entrench above-target inflation. This risk however appears relatively short-lived in both countries since the indicator starts receding along the tightening cycle and the subsequent moderation in realized inflation following the 2022 peak.

Strikingly, while the anchoring indicator in Canada has remained well below the unanchoring threshold since then, it has risen again in the US, particularly in the most recent data in 2025. Within the context of our simple model, this discrepancy between the two countries reflects distinct movements in realized inflation and output gap. While inflation in Canada has landed around its two-percent target amid downward pressures from aggregate demand (negative output gaps), inflation in the US still shows some sign of persistence above the target amid expansionary pressures from positive output gaps (see, again, [Figure 2](#)).

Overall, our estimation results demonstrate time variation in the prevalence of the risk of

expectations unanchoring.

Finally, to relate our model-based interpretation of inflation expectations to empirical inflation expectations, Figures 3a and 3b report the model-implied time series of aggregate inflation expectations based on the estimated values of the autoregressive parameters ϕ_j in Cols. (V) and (X) of Table 1, together with households' expectations data from the corresponding country. We focus on the period from 2015 to 2025, over which expectation data are available for both countries at a quarterly frequency. We report the median one-year-ahead inflation expectations together with their interquartile range in each quarter, obtained from the University of Michigan Survey of Consumers (MSC) for the US and the Bank of Canada's Canadian Survey of Consumer Expectations (CSCE).

The series of model-implied expectations and the anchoring indicator dovetail neatly with the actual expectations of households; for convenience, Fig. 2b displays the time series of this indicator over the same period as the expectations data. As aforementioned, before 2020 the estimated anchoring indicator hovers below the unanchoring threshold, which aligns with the IQR boxes clustered around the two-percent target, albeit with the well-documented upward bias in household expectations (see, for example, Ehrmann et al. 2017; D'Acunto et al. 2023). This pattern is consistent with our model-based analysis suggesting well-anchored inflation expectations during this time period, including the 2010 decade.

Focusing on the post-COVID-19 inflation surge, our estimates of the anchoring indicator breaching the threshold in both countries is also in line with the IQR boxes widening and the upper quartile lifting upward sharply. This dynamics mirrors the model-based diagnosis of a heightened unanchoring risk, with more dispersed and higher model-implied expectations. Along the disinflation after 2022Q2, the median expectations in both countries also fall, which is again consistent with the gradual fall in the anchoring indicator.¹⁵

¹⁵The large dispersion in the MSC series in April 2025 is consistent with partisan composition effects that are typically not part of the sampling weights, as discussed in Hajdini et al. [2025]: respondents' inflation

The figure therefore confirms that the estimated movements in the anchoring indicator map onto observable shifts in real-world expectation level and dispersion, without requiring any expectation data to estimate this indicator.

4 Conclusion

We estimate a model of inflation beliefs that contains an indicator of expectations anchoring that varies over the business cycle using US and Canadian data. We find that a mean-reverting and a trend-chasing belief-formation process co-exist and their relative dominance varies as a function of the realized inflation gap to its target. The resulting time-varying mean-reversion coefficient summarizes expectations anchoring: when inflation is low and stable, it remains below one, which describes anchored expectations on average, whereas fundamental shocks may push inflation and average expectations away from the target, which carries a risk of expectations unanchoring.

While the overall inflation dynamics in the US and Canada over the recent decades are consistent with mean-reverting (anchored) expectations, we identify episodes during which macroeconomic data reject mean reversion and instead indicate a shift toward their unanchoring. This risk materialized particularly between 2021Q3 and 2022Q3 in both countries, before dissipating, quickly in Canada and with more sluggishness in the US. Interestingly, we do not find any evidence of an unanchoring risk on the downside during the 2010s decade when policy concerns emphasized such a risk amid below-target inflation and interest rates at the ELB in the US. This suggests that the unanchoring risk is asymmetric, i.e. steeper on the upside in the wake of inflationary shocks than on the downside when inflation lingers below target. Admittedly, the recent history does not include a

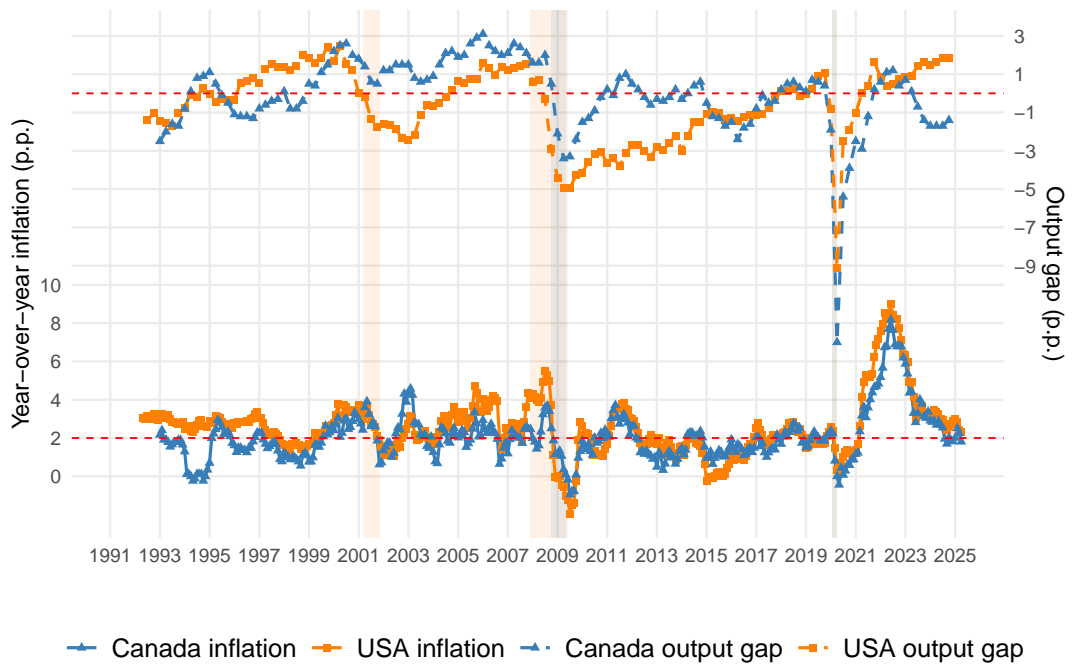
views differ sharply by political affiliation, and the MSC sample around 2025Q2 tilts toward a rising share Democrat-leaning respondents who, at that time, were reporting higher inflation expectations. This effect accounts for about 2 p.p. of the median expectation and widens the spread across respondents.

low-inflation episode of comparable length and magnitude to the post-pandemic inflation surge in terms of deviation from inflation target, which might also contribute to this asymmetry.

In terms of policy lesson, our results do not confirm the prevailing concerns in the 2010s about the risk of expectation unanchoring on the downside, even at the ELB. In terms of modeling, this finding supports the use of asymmetric loss functions rather than the traditional quadratic and, hence, symmetric ones (see, e.g., [Capistrán and Timmermann 2009](#)). Our framework can also be extended to think of how monetary policy can influence forecasting behaviors beyond its effects on realized inflation. For instance, CB actions and communication may directly influence agents' level of attention or speed of switching between alternative forecasting rules. These model parameters could also depend on the credibility of the target and the level of inflation itself.

Our stylized framework offers an easy tool to monitor inflation dynamics and carries clear policy guidance: whenever model estimates signal that the anchoring indicator approaches the unanchoring threshold, the risk of expectation unanchoring may become a first-order concern for the central bank. Such a risk may then call for a swift policy tightening to avoid falling behind the curve. Of course, we envision this anchoring indicator as a diagnostic measure rather than a mechanical trigger rule. In practice, it is meant to be an additional tool in a large toolbox of, among other things, quantitative model insights, qualitative evidence from surveys, and judgment of the policy makers which may include, e.g., concerns about financial stability, employment, fiscal conditions, or external shocks, in addition to inflation expectations. This simple tool, however, only requires macroeconomic data, which circumvents the well-known issues associated with expectation data; for instance, disparities between household, firm, professional or market-based data, systematic biases, or noise in survey data. Our framework is then also straightforwardly applicable to contexts where expectation data are unavailable.

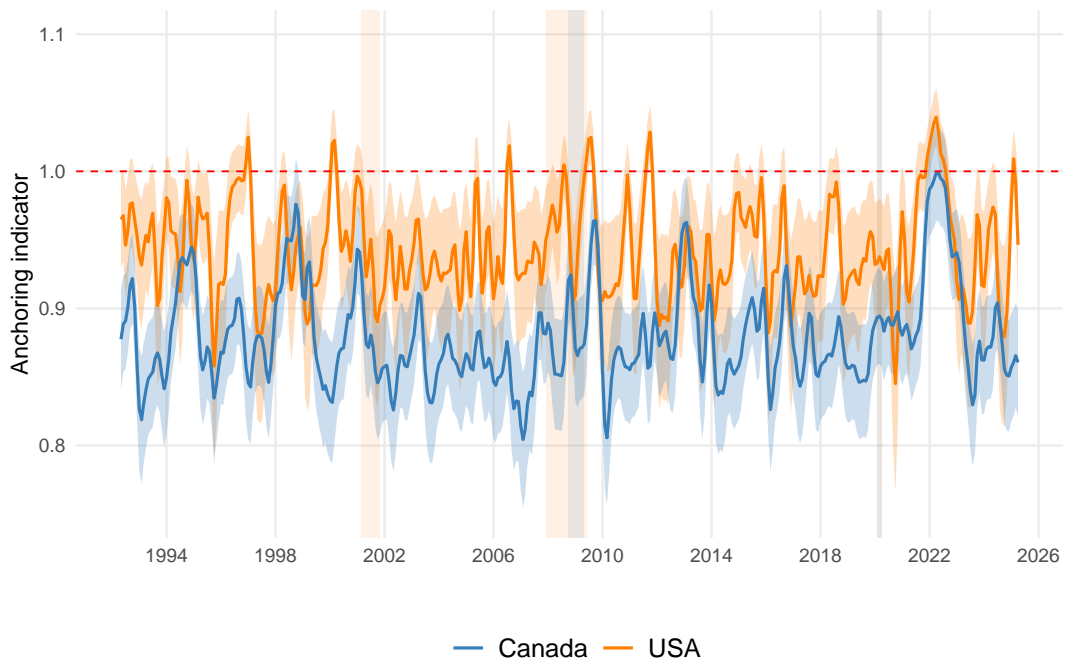
Figure 1: Inflation and output gap in the US and Canada



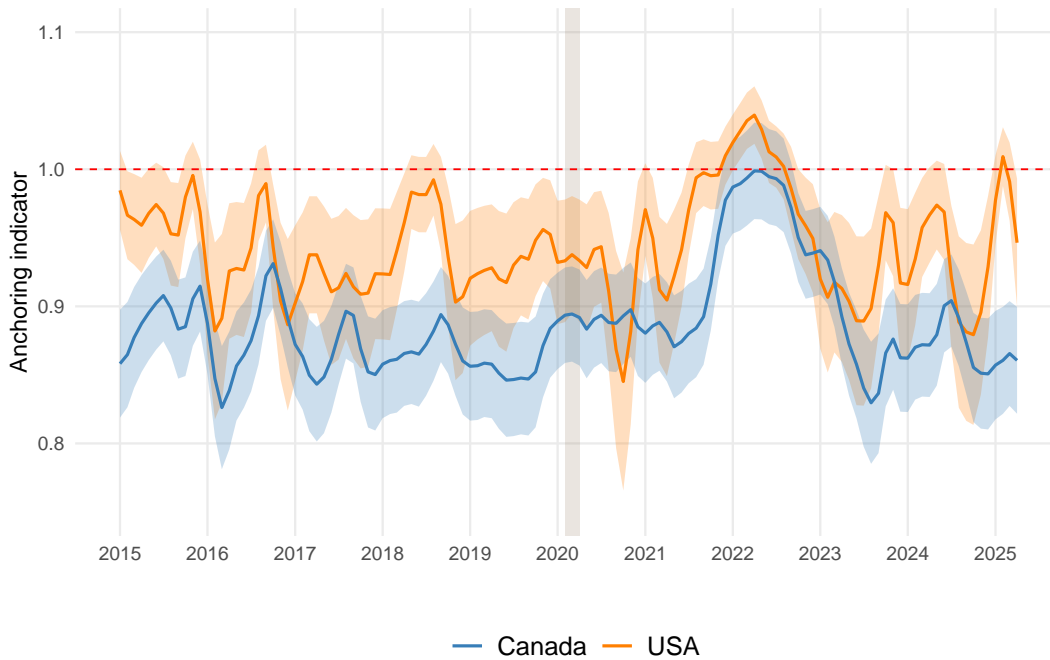
Notes: The shaded light orange (respectively blue) vertical columns are recessionary episodes in the US (respectively Canada) as identified by the NBER's US Business Cycle Expansions and Contractions (respectively the C.D. Howe Institute).

Figure 2: Dynamics of expectation anchoring in the US and Canada

(a) Entire sample



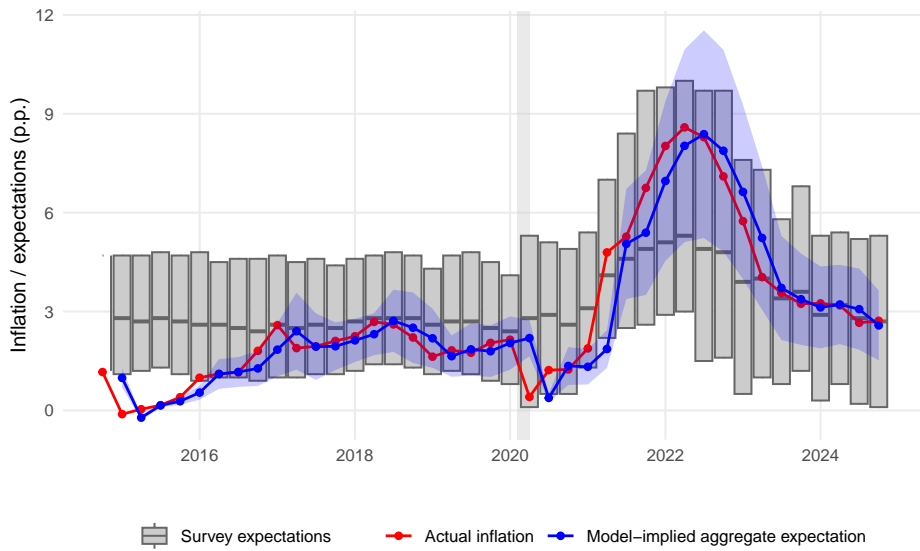
(b) Zoom in the past 10 years



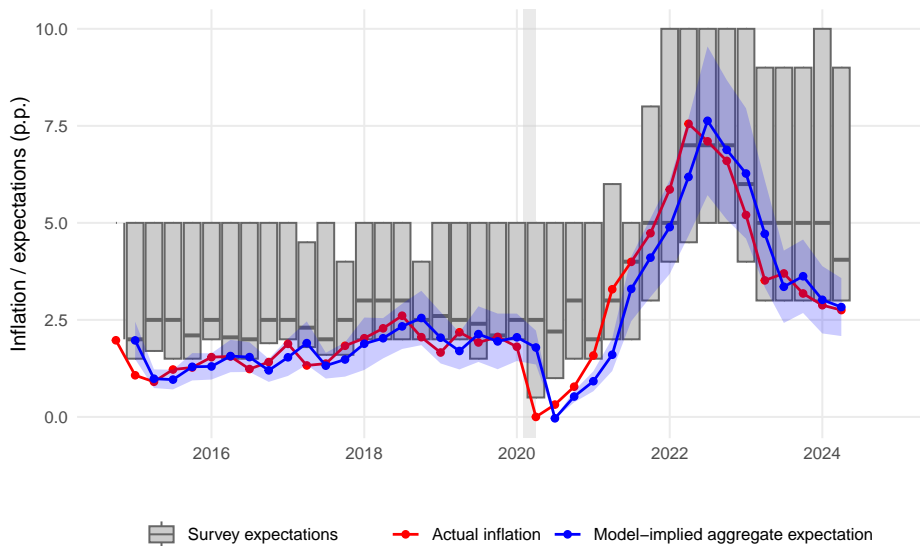
Notes: The anchoring indicator series ρ_t are computed using the estimated parameters in Columns (I) and (VI) of Table 1 for the US and Canada, respectively. The shaded areas represent the 95% confidence intervals. The dashed horizontal line represents the anchoring threshold, and the vertical shade areas the recessions over the samples.

Figure 3: Survey v.s. model-implied expectations

(a) USA



(b) Canada



Notes: Survey expectation data are taken from University of Michigan Survey of Consumers (MSC) for the US (up until 2024Q4), and from the Bank of Canada's Canadian Survey of Consumer Expectations (CSCE), starting from its introduction in 2014Q4, with the latest data available for 2024Q2. The gray horizontal bars represent the median one-year-ahead expectations, together with the second and third quartiles in the gray boxes (corresponding to the interquartile range, IQR). The shaded blue area represents the 95% confidence interval of the model-implied aggregate expectation series, computed using the estimated values ϕ_1 and ϕ_2 in Columns (V) and (X) of Table 1 at a quarterly frequency.

Table 1: NLS estimates of the behavioral model

Parameters	United States										Canada									
	Baseline					Baseline					Baseline					Baseline				
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
ϕ_1	0.779*** (0.094)	0.777*** (0.095)	0.721*** (0.092)	0.658** (0.265)	-0.227 (0.245)	0.625*** (0.081)	0.708*** (0.101)	0.790*** (0.121)	0.708*** (0.157)	0.390*** (0.145)	0.779*** (0.095)	0.777*** (0.095)	0.721*** (0.092)	0.658** (0.265)	-0.227 (0.245)	0.625*** (0.081)	0.708*** (0.101)	0.790*** (0.121)	0.708*** (0.157)	0.390*** (0.145)
$\Delta\phi$	0.318*** (0.120)	0.320*** (0.120)	0.477*** (0.106)	0.512* (0.284)	2.107*** (0.254)	0.506*** (0.124)	0.410** (0.208)	0.358** (0.134)	0.427* (0.253)	1.020*** (0.170)	0.318*** (0.120)	0.320*** (0.120)	0.477*** (0.106)	0.512* (0.284)	2.107*** (0.254)	0.506*** (0.124)	0.410** (0.208)	0.358** (0.134)	0.427* (0.253)	1.020*** (0.170)
$\phi_2 (= \phi_1 + \Delta\phi)$	1.097*** (0.032)	1.097*** (0.034)	1.198*** (0.096)	1.171*** (0.037)	1.879*** (0.059)	1.131*** (0.052)	1.118*** (0.113)	1.148*** (0.042)	1.135*** (0.108)	1.411*** (0.083)	1.097*** (0.032)	1.097*** (0.034)	1.198*** (0.096)	1.171*** (0.037)	1.879*** (0.059)	1.131*** (0.052)	1.118*** (0.113)	1.148*** (0.042)	1.135*** (0.108)	1.411*** (0.083)
β	1.750*** (0.583)	1.741*** (0.663)	1.147*** (0.418)	1.729*** (0.621)	1.586*** (0.294)	1.391*** (0.396)	1.285* (0.708)	1.365* (0.777)	1.223* (0.699)	1.612*** (0.245)	1.750*** (0.583)	1.741*** (0.663)	1.147*** (0.418)	1.729*** (0.621)	1.586*** (0.294)	1.391*** (0.396)	1.285* (0.708)	1.365* (0.777)	1.223* (0.699)	1.612*** (0.245)
δ	0.000 (0.441)	—	—	—	—	0.572*** (0.143)	—	—	—	—	0.000 (0.441)	—	—	—	0.572*** (0.143)	—	—	—	—	—
κ	-0.008 (0.013)	-0.008 (0.013)	-0.035 (0.049)	-0.007 (0.015)	0.003 (0.011)	-0.041*** (0.012)	-0.033*** (0.012)	-0.007 (0.035)	-0.034 (0.023)	0.004 (0.013)	-0.008 (0.013)	-0.008 (0.013)	-0.035 (0.049)	-0.007 (0.015)	0.003 (0.011)	-0.041*** (0.012)	-0.033*** (0.012)	-0.007 (0.035)	-0.034 (0.023)	0.004 (0.013)
F-test: $H_0 : \phi_1 + \Delta\phi = 1$	8.938***	8.159***	4.299**	21.088***	218.935***	6.221**	1.095	12.129***	1.574	24.569***	8.938***	8.159***	4.299**	21.088***	218.935***	6.221**	1.095	12.129***	1.574	24.569***
Sample	All	All	2020M4-	2007M1-	All	All	All	2020M4-	2007M1-	All	All	All	2020M4-	2007M1-	All	All	All	2020M4-	2007M1-	All
Num.Obs.	410	410	61	220	135	410	410	61	220	135	410	410	61	220	135	410	410	61	220	135
BIC	428.1	422.0	95.8	285.5	41.5	498.5	496.5	107.5	272.8	24.1	428.1	422.0	95.8	285.5	41.5	498.5	496.5	107.5	272.8	24.1
Log.Lik.	-195.977	-195.979	-37.630	-129.271	-8.463	-231.213	-233.229	-43.489	-122.904	0.225	-195.977	-195.979	-37.630	-129.271	-8.463	-231.213	-233.229	-43.489	-122.904	0.225

Notes: HAC standard errors in parentheses. The variance of ϕ_2 accounts for variance and covariance of ϕ_1 and $\Delta\phi$ (the covariance is negative in all cases). κ is expected to be negative when activity is measured by the unemployment gap and positive when measured by the output gap. "All" indicate the full samples (1991M3–2025M4). Row "F-test: $H_0 : \phi_1 + \Delta\phi = 1$ " reports the Wald F -statistic for the joint null hypothesis $\phi_1 + \Delta\phi = 1$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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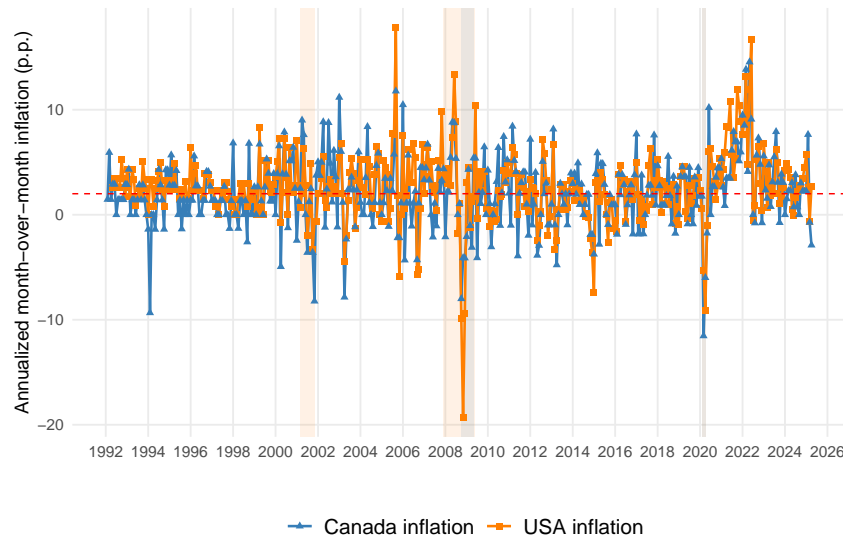
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Appendix

Estimation results with month-over-month (seasonally adjusted) annualized inflation

Figure A1: Annualized (seasonally adjusted) month-over-month inflation in the US and Canada



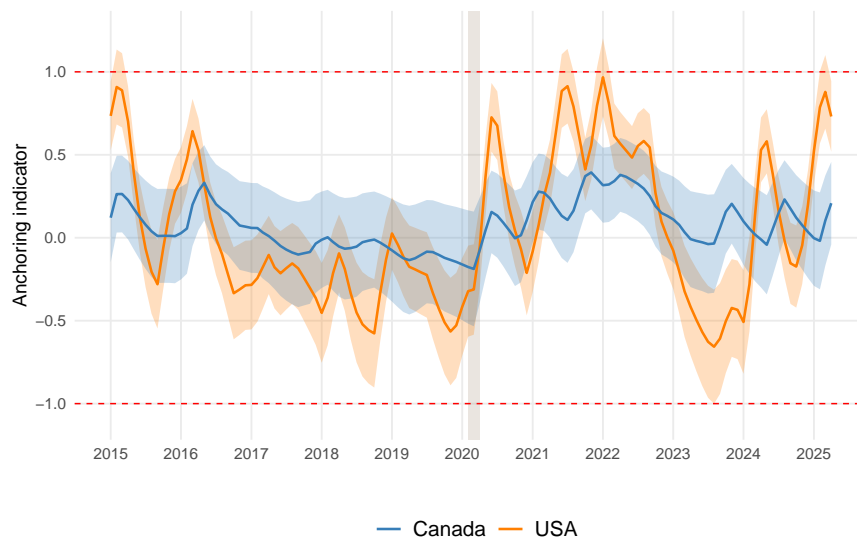
Notes: The shaded light orange (respectively blue) vertical shaded areas are recessionary episodes in the US (respectively Canada) as identified by the NBER's US Business Cycle Expansions and Contractions (respectively the C.D. Howe Institute). Monthly frequency. Data obtained from the same source mentioned in the manuscript.

Table A1: NLS estimates of the behavioral model (1992M5–2025M4) using annualized (seasonally adjusted) month-over-month inflation

Parameters	<i>United States</i>	<i>Canada</i>
	(I)	(II)
ϕ_1	-0.943*** (0.362)	-0.429 (0.383)
$\Delta\phi$	4.991*** (1.162)	5.425** (2.137)
$\phi_2 (= \phi_1 + \Delta\phi)$	4.048*** (0.856)	4.996*** (1.819)
β	5.691** (2.531)	4.401** (1.729)
δ	0.773*** (0.045)	0.862*** (0.044)
κ	-0.182* (0.107)	-0.203* (0.118)
F-test: $H_0 : \phi_1 + \Delta\phi = 1$	12.69***	4.83**
Num.Obs.	396	396
BIC	2132.5	2098.4
Log.Lik.	-1048.284	-1031.262

Notes: See Table 1.

Figure A2: Dynamics of expectation anchoring in the US and Canada (2015-2025) using estimations from annualized month-over-month inflation



Notes: See Figure 2. The anchoring indicator series ρ_t is computed, for each country, using the estimated parameters in Columns (I) and (II) of Appendix Table A1 for the US and Canada, respectively.

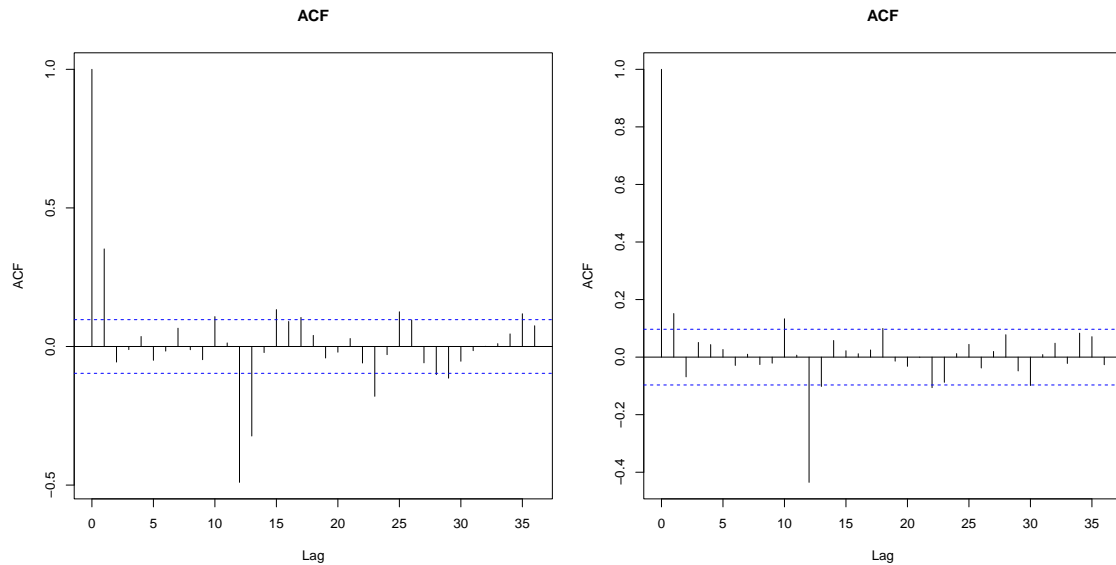
Additional results: baseline specification

Table A2: Unit root and stationarity tests for inflation gap and unemployment gap (1991M3-2025M4)

	<i>United States</i>		<i>Canada</i>	
	(I) Inflation gap	(II) Unemployment gap	(III) Inflation gap	(IV) Unemployment gap
p-value: ADF test	0.038	0.016	0.008	0.007
p-value: Phillips-Perron test	0.039	0.086	0.010	0.073
p-value: KPSS test	≥ 0.10	≥ 0.10	≥ 0.10	≥ 0.10
90% C.I. for the largest AR root	0.910 – 0.990	0.840 – 0.990	0.720 – 0.980	0.700 – 0.980

Notes: p-values are from the augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and KPSS tests for each series. ADF tests the unit-root null against stationarity (we use up to 24 lags, where the lag length is chosen with the BIC). PP tests the unit-root null with HAC variance estimation. KPSS tests the null of stationarity around a constant mean. The last row reports the 90% confidence interval for the largest autoregressive (AR) root, computed using [Stock \[1991\]](#)’s method of inverting the ADF test statistic. All test results support stationarity, and the 90% C.I. of the largest AR root for all four series do not include a unit root. Additionally, the OCSB (Osborn–Chui–Smith–Birchenhall) test rejects a seasonal unit root at the 5% level for all four series.

Figure A3: ACF of the residuals of models (I) and (VI) in Table 1, for the United States (left) and Canada (right)



Sensitivity analyses

Table A3: GMM/IV estimates of the behavioral model

Parameters	Instrument sets					
	<i>United States</i>			<i>Canada</i>		
	(I) <i>Z</i> (12)	(II) <i>Z</i> (18)	(III) <i>Z</i> (24)	(IV) <i>Z</i> (12)	(V) <i>Z</i> (18)	(VI) <i>Z</i> (24)
ϕ_1	0.334 (0.658)	0.379 (0.348)	0.180 (0.314)	-0.207 (0.571)	-0.422 (1.004)	-0.612 (0.774)
ϕ_2	1.180*** (0.414)	1.207*** (0.150)	1.263*** (0.227)	1.114*** (0.263)	1.461*** (0.529)	1.558*** (0.392)
β	1.525*** (0.540)	1.579*** (0.419)	1.554*** (0.264)	2.974* (1.804)	1.935*** (0.285)	1.868*** (0.200)
δ	0.479 (0.480)	0.199 (0.407)	0.437 (0.286)	0.480 (0.380)	0.718*** (0.204)	0.541*** (0.184)
κ	-0.027* (0.016)	-0.028** (0.012)	-0.017 (0.011)	-0.079*** (0.024)	-0.038* (0.021)	-0.023 (0.021)
F-test: $H_0 : \phi_2 = 1$	0.189	1.908	1.351	0.190	0.759	2.031
Num.Obs	383	383	383	383	383	383
Hansen J p-value	0.083	0.269	0.491	0.027	0.170	0.397

Notes: See Table 1. $Z(L)$ denotes the instrument set including L lags of the inflation and unemployment gaps.

Table A4: Sensitivity analysis to values of the discount factor γ

Parameters	United States				Canada			
	Baseline	(II)	(III)	(IV)	Baseline	(VI)	(VII)	(VIII)
	$\gamma = 0.996$	$\gamma = 0.997$	$\gamma = 0.998$	$\gamma = 0.999$	$\gamma = 0.996$	$\gamma = 0.997$	$\gamma = 0.998$	$\gamma = 0.999$
ϕ_1	0.779*** (0.094)	0.785*** (0.090)	0.782*** (0.092)	0.794*** (0.089)	0.625*** (0.081)	0.552*** (0.096)	0.572*** (0.087)	0.547*** (0.096)
$\Delta\phi$	0.318*** (0.120)	0.306*** (0.117)	0.309** (0.121)	0.287** (0.119)	0.506*** (0.120)	0.609*** (0.136)	0.580*** (0.125)	0.614*** (0.137)
$\phi_2 (= \phi_1 + \Delta\phi)$	1.097*** (0.032)	1.090*** (0.034)	1.091*** (0.035)	1.081*** (0.039)	1.131*** (0.052)	1.161*** (0.051)	1.151*** (0.051)	1.161*** (0.052)
β	1.750*** (0.583)	1.896*** (0.649)	1.852*** (0.625)	1.995** (0.850)	1.391*** (0.396)	1.307*** (0.412)	1.316*** (0.455)	1.292*** (0.407)
δ	0.000 (0.441)	0.000 (0.426)	0.000 (0.432)	0.000 (0.409)	0.572*** (0.143)	0.580*** (0.121)	0.578*** (0.127)	0.578*** (0.122)
κ	-0.008 (0.013)	-0.008 (0.013)	-0.008 (0.013)	-0.007 (0.013)	-0.041*** (0.012)	-0.045*** (0.013)	-0.044*** (0.013)	-0.045*** (0.013)
F-test: $H_0 : \phi_1 + \Delta\phi = 1$	8.938***	7.020***	6.612**	4.235**	6.221**	9.883***	8.942***	9.632***
Num.Obs.	410	410	410	410	410	410	410	410
BIC	428.1	428.1	428.3	428.4	498.5	498.4	498.5	498.5
Log.Lik.	-195.977	-196.021	-196.091	-196.162	-231.213	-231.172	-231.203	-231.209

Notes: See Table 1.

Table A5: Sensitivity analysis by the memory length K (months)

Parameters	United States				Canada			
	Baseline	(II)	(III)	(IV)	Baseline	(VI)	(VII)	(VIII)
	$K = 12$	$K = 18$	$K = 24$	$K = 36$	$K = 12$	$K = 18$	$K = 24$	$K = 36$
ϕ_1	0.779*** (0.094)	0.789*** (0.089)	0.805*** (0.084)	0.783*** (0.090)	0.625*** (0.081)	0.664*** (0.101)	0.628*** (0.079)	0.626*** (0.079)
$\Delta\phi$	0.318*** (0.120)	0.301*** (0.115)	0.276** (0.107)	0.312*** (0.117)	0.506*** (0.120)	0.455** (0.182)	0.500*** (0.117)	0.501*** (0.118)
$\phi_2 (= \phi_1 + \Delta\phi)$	1.097*** (0.032)	1.090*** (0.033)	1.081*** (0.030)	1.095*** (0.034)	1.131*** (0.052)	1.119*** (0.092)	1.128*** (0.052)	1.127*** (0.053)
β	1.750*** (0.583)	1.962*** (0.681)	2.137*** (0.803)	1.873*** (0.632)	1.391*** (0.396)	1.460** (0.577)	1.421*** (0.409)	1.435*** (0.414)
δ	0.000 (0.441)	0.000 (0.413)	0.000 (0.386)	0.000 (0.401)	0.572*** (0.143)	0.549*** (0.164)	0.567*** (0.145)	0.577*** (0.144)
κ	-0.008 (0.013)	-0.008 (0.013)	-0.007 (0.013)	-0.008 (0.013)	-0.041*** (0.012)	-0.037*** (0.012)	-0.041*** (0.012)	-0.041*** (0.012)
F-test: $H_0 : \phi_1 + \Delta\phi = 1$	8.938***	7.290***	7.287***	7.947***	6.221**	1.677	6.023**	5.744**
Num.Obs.	410	410	410	410	410	410	410	410
BIC	428.1	427.6	427.3	427.5	498.5	498.4	498.2	497.9
Log.Lik.	-195.977	-195.738	-195.613	-195.699	-231.213	-231.128	-231.052	-230.881

Notes: See Table 1.

Table A6: Baseline NLS estimates of the behavioral model with different standard-error corrections

Parameters	<i>United States</i>				<i>Canada</i>			
	Baseline (I)	Pre-whi. (II)	12-lags (III)	HCCME (IV)	Baseline (V)	Pre-whi. (VI)	12-lags (VII)	HCCME (VIII)
ϕ_1	0.779*** (0.094)	0.779*** (0.094)	0.779*** (0.094)	0.779*** (0.097)	0.625*** (0.081)	0.625*** (0.082)	0.625*** (0.090)	0.625*** (0.109)
$\Delta\phi$	0.318*** (0.120)	0.318*** (0.120)	0.318** (0.124)	0.318** (0.136)	0.506*** (0.120)	0.506*** (0.124)	0.506*** (0.137)	0.506*** (0.165)
$\phi_2 (= \phi_1 + \Delta\phi)$	1.097*** (0.032)	1.097*** (0.032)	1.097*** (0.038)	1.097*** (0.051)	1.131*** (0.052)	1.131*** (0.055)	1.131*** (0.059)	1.131*** (0.069)
β	1.750*** (0.583)	1.750*** (0.576)	1.750** (0.693)	1.750** (0.828)	1.391*** (0.396)	1.391*** (0.417)	1.391*** (0.532)	1.391** (0.548)
δ	0.000 (0.441)	0.000 (0.435)	0.000 (0.375)	0.000 (0.271)	0.572*** (0.143)	0.572*** (0.144)	0.572*** (0.147)	0.572*** (0.133)
κ	-0.008 (0.013)	-0.008 (0.013)	-0.008 (0.017)	-0.008 (0.015)	-0.041*** (0.012)	-0.041*** (0.013)	-0.041** (0.017)	-0.041** (0.019)
F-test: $H_0 : \phi_1 + \Delta\phi = 1$	8.938***	9.113***	6.326**	3.671*	6.221**	5.737**	5.400**	3.629*
Num.Obs.	410	410	410	410	410	410	410	410
BIC	428.1	428.1	428.1	428.1	498.5	498.5	498.5	498.5
Log.Lik.	-195.977	-195.977	-195.977	-195.977	-231.213	-231.213	-231.213	-231.213

Notes: See Table 1. ‘Baseline’ columns report HAC standard errors. ‘Pre-whi.’ columns report prewhitened-HAC standard errors. ‘12-lags’ columns report HAC with a bandwidth of 12 lags. ‘HCCME’ columns report White’s heteroscedasticity-consistent covariance matrix estimator (HCCME) standard errors.