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# **A Measure of our Uncertainty: Households' Inflation Expectation and Information Shocks**

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DOCUMENTO DE TRABAJO N° 273

Septiembre de 2023

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**Galará, Ignacio (2023). A Measure of our Uncertainty: Households' Inflation Expectation and Information Shocks. *Documento de trabajo RedNIE N°273.***

# A measure of our uncertainty: Households' inflation expectation and information shocks

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June 28, 2023

## Abstract

This work focus on understanding deeper how the general public form their inflation expectations, addressing the importance of having well (micro)founded models to forecast consumer's inflation expectations, not only for inflationary countries (like some developing ones) or inflationary contexts (like the one that begins after COVID-19 pandemic), but also when there exist some information breaks driven by specific global or national events. By a proposed VAR *structural model* based on behavioral mechanisms, and a state-space model based on Bayesian's principles, I use data from Argentina and the US to retrieve a latent variable of attention to own beliefs and to outside information, which proves to be related to information outbreaks, and that correlates with different uncertainty measures, specially during those breaks.

JEL: *E31; D84; C11; C32*

## 1 Introduction

There's a common agreement among economists that it doesn't make much of a sense to forecast inflation with very sophisticated models, given that it has shown to behave most likely as a random walk, so a simple AR model will suffice to do a good job (Atkeson, Ohanian, et al., 2001; Canova, 2007; Stock and Watson, 1999). However, when it comes to forecasting actual inflation expectations it may not be that straight forward, because they will most likely be driven by psychological components related to both information processing mechanisms and the quality of that information. In particular, one expect to have some problems when referring to consumers' expectations, who are less informed than professionals, specially if there exist uncertainty or some information restrictions in specific periods.

During periods marked by uncertainty, agents are forced to take heterogeneous subsets of information which may be incomplete and/or imperfect. Then, the way information is processed, the subsets of information chosen and the decision-making context become determining factors in shaping consumers' expectations and behaviors, favoring certain rationality biases. The latter is a essential element to take into consideration when studying and trying to anticipate consumers' decisions, fundamentally consumption and savings; undoubtedly, no matter how well forecasted inflation is by Central Banks or professionals, what matters in the end is what people believe, and this will be shaped by many different factors.

Another important fact that is worth reviewing is that data shows that annual expected inflation, both from professionals and households, hardly match actual observed inflation for the forecasted period; but also, those expectations doesn't match either among them, while the former tends to be smoother and less volatile, the latter usually exhibit a much more pessimist position, almost always over professionals' (Figures 1 and 2).

This aspect of expectation anchoring to external information sets is well covered in Weber, 2022, were the author stress the difficulties of US households to properly asses which is the inflation target by the FED, and also that they typically overestimate future inflation relative to ex-post realizations. As there exist heterogeneity on responses, the degree of overestimation depends on who answers the survey. Those who are more likely to face the volatility of price at the grocery stores overestimate the most; being this the main

source on which inflation expectations are built, followed by "family and friends opinion", "TV and radio" (in general), and then "newspaper" and "online news". With this background it is expected to observe significant mismatch between expectations and realizations of inflation, leaving room to explore deeper these expectation formation mechanisms.

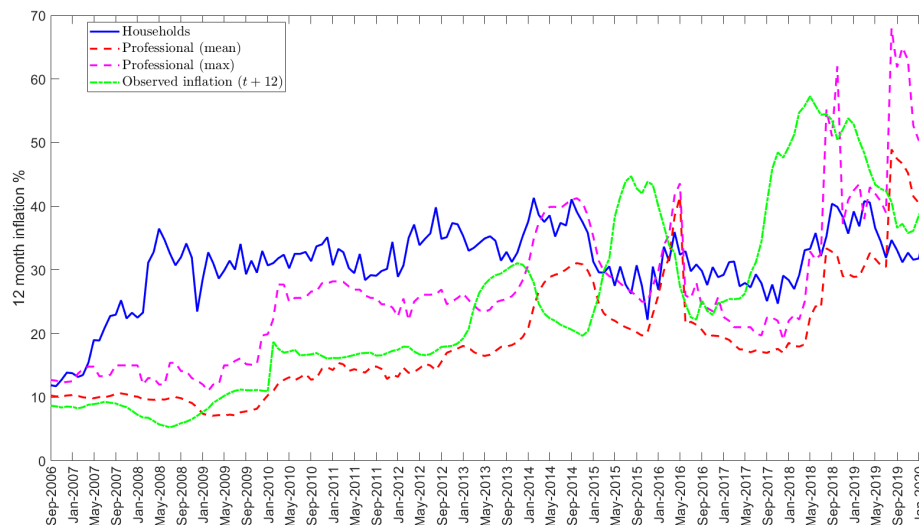


Figure 1: Annual expected inflation and observed inflation for the forecasted period for Argentina

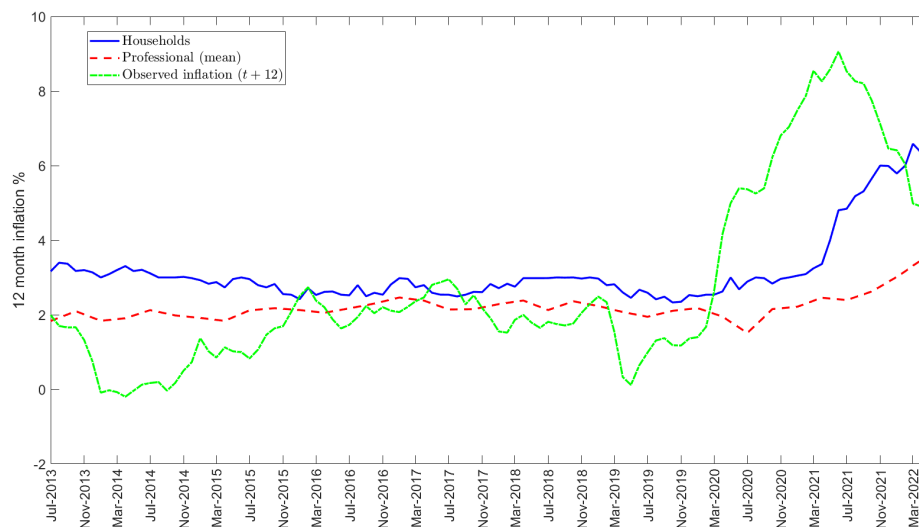


Figure 2: Annual expected inflation and observed inflation for the forecasted period for USA

For this work I built two data sets, one for Argentina, considering it a country with structural inflation for the past 15 years, from Sep-2006 till May-2023<sup>1</sup>, and data for the US, as a benchmark analysis, from Jul-2013 to May-2023, based on availability of information at the levels of detail needed. In order to explore the data I start with simple descriptive statistics for time series, and trying to fit ARIMA models for expected inflation by consumers, these discarded a white noise behavior, neither for Argentina or the US, instead

<sup>1</sup>In this work I'll use only data to March 2020 for Argentina, due to COVID-19 outbreak which breaks every information set and need a treatment out of the scope of this paper.

it exhibits stationarity, with no unit root for the period studied, that could be modeled with an ARMA process, however with room for improvement. Then I apply a behavioral model I proposed in previous studies (Galará, 2021) to get some long-run structure of inflation expectations' DGP and, with those results, I use the methodology proposed by Lamla and Sarferaz, 2012 (refined), built in a Bayesian framework and using Kalman-filter to retrieve latent variables related to households' degree of *attention* to their own beliefs.

This *attention* dynamic parameter can be contrast with some well-known, well-identified, and relevant events that generates information breakups for each country and the world, showing that attention shifted from own beliefs to external sources during those periods, as a sign that people search for more information whenever a not known scenario (or the menace of one) shows up. Then, I compare it with different uncertainty indexes proving a non-negligible relationship between uncertainty and *attention*, however with opposed conclusions for each country. While in the US a rise in uncertainty implies in general a drop in the attention to own beliefs, in Argentina people strengthen their position to their own beliefs, disregarding outside information. The estimation methodology also retrieves the variance of our parameter of interest, which can be read as attentions' updating speed, a useful measure to contrast with uncertainty, so the same exercises are ran with this variable with interesting results.

## 2 Data

For this study I use monthly data for expected inflation by households, for Argentina it is provided by the Finance Research Center of the Torcuato Di Tella University, corresponding to their Inflation Expectations Survey (IE). This Center also measure a Consumer Confidence Index (ICC) and a Government Confidence Index (ICG), which will be proxies of the households' perception of the macroeconomic context. The US counterparts are the expected inflation from the Survey of Consumer Expectations of the NY FED, and the Consumer Sentiment (CSI) and Economic Situation (ESI) indexes from the Consumer Opinion Survey run by the University of Michigan.

The external information on inflation is taken from the Market Expectations Survey (MES) of the Central Bank of Argentina, getting the average forecast of professionals on inflation for the next twelve months, and also its standard deviation, maximum, and the number of respondents. For the US we have the Survey of Professional Forecasters run by the FED of Philadelphia, from which I recovered the same indicators with exception to the maximum forecast.

A side note for Argentina is needed. There were several events that impact over the availability of inflation information in different periods and ways: INDEC's intervention by the central government (Jan-07); the prohibition to publish other price statistics than the official one (Oct-12) with the interruption of the Central Bank's MES publications; a change of government and CPI methodological revision (Nov-15); a new publication of the INDEC CPI (May-16), among others. Those events specially impacted over the inflation forecast by professional, truncating it series, so that data needed to be built for the period between Oct-12 to Dec-15 (to further information about this complete process refer to Galará, 2021). However this has an important impact over the information set needed for this model, it demonstrate the strength of this framework because it is based only on whatever information households have available; the quality or consistency of the information is not relevant because *people have to take decisions with what they have*. Also, this information breakups are interesting to study what happened with households' beliefs and attention at the moment the information scenario changes, and while uncertainty last.

Finally, for measuring uncertainty I used the IMF's World Uncertainty Index (WUI), available on a monthly frequency since Jan-2008, and it sub-series for Argentina and the US<sup>2</sup>. For the US I also take a news-based index for the United States (Economic Policy Uncertainty Index), measured by St. Luis' FED. At last, for the purpose of this paper, I choose to build an other index using the methodology of principal components, available in the Matlab toolbox of Ferroni and Canova, 2021, using data from Google Trends about the searching relevance of specific economic-uncertainty related terms: "economy", "inflation", "dollar", "crisis", "government", for both countries, and adding "war" specifically for the US; I extracted one principal component (the most relevant), and re-scale it to build an index.

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<sup>2</sup>The US set is discarded due to high correlation with the WUI, given the relevance of this country on the overall index (each country is weighted by their GDP).

## 2.1 ARIMA analysis

In line to the hypothesis that inflation and its derivatives tend to follow a random-walk process, I tested the household expected inflation for both countries with time-series tools, and try to fit an AR (or ARIMA) model to forecast the data. From Figures 1 and 2 we can see that the data seems to follow a random-walk and that it is most likely stationary.

For Argentina, the ACF shows a gradual decay till lag 15, although it increases after lag 20, and PACF decline after 2 lags, indicating at least an AR(2) process. The Portmanteau test for white noise is rejected at all levels of significance, and the ADF test discard a non-stationary process. After some analysis, the model that best fit the data is an ARMA(2,2) (first column of table 1). For the US, there's also a (much more) gradual decay of the ACF and the PACF only report 1 lag as relevant. The process is discarded to be white-noise and non-stationary, so the best fitted model is an AR(1) (second column of table 1).

Model	AR(1)	AR(2)	MA(1)	MA(2)	Cons	N	Log-lik
Argentina	1.81 (0.2755)	-0.82 (0.2633)	-1.15 (0.2824)	0.29 (0.1013)	29.5 (2.59)	163	-387.64
US	0.98 (0.0158)				3.47 (0.23)	119	6.072

Table 1: ARMA models for  $EI_t$  Argentina and the US

Even though these results seems to left nothing else to say, in next sections we will see that this DGP can be better modeled with specifications that improve the fit of data with big advantages over this ARMA models. The first one is that those process only deliver good predictions of expected inflation at period  $t$  after one or two periods forward, being too myopic to take into account the updating process within a month and at information shocks, which are the main aspect of these research. Additionally, after applying our state-space specification, we will be able to recover the latent variable of interest and perform further empirical analysis.

## 3 The behavioral model

We can use our aggregate time-series data and implement Lamla and Sarferaz, 2012 and Galará, 2021 framework, to analyze how attentive people are to information about inflation, whether this attention changes over time, and the factors that influence this dynamic.

In the model we have that, at the beginning of month  $t$  agent  $i$  holds an initial belief about what future inflation will be (prior); this belief is assumed to be  $\pi_{i,t} \sim N(\pi_{i,t}, \sigma_a^2)$ . During that month the agent observes a  $V$  number of news items that have noisy information about the future of inflation. The received noisy signal can be modeled as  $\psi_{v,t} \sim N(\theta_t, \sigma_{\psi,t}^2)$  from which the (clean) signal about the inflation prediction must be extracted, in this case the parameter to identify is  $\theta_t$ , which can be a prediction made by professionals, and can be interpreted as the average of predictions of all experts.

Since we have a belief (prior),  $V$  news with noisy reports ( $\psi_{v,t}$ ) to infer  $\theta_t$ , we have to solve a problem based on Bayes' rule:

$$k_i(\pi_{i,t+1}|\psi_{v,t}) \propto \prod_{v=1}^V f_i(\psi_{v,t}|\pi_{i,t})h(\pi_{i,t}) \quad (1)$$

Where  $h(\cdot)$  is the marginal density function of the prior,  $f_i(\cdot)$  is the conditional density function of the observed public information given the prior, and  $k_i(\cdot)$  is the density of the posterior given the  $V$  noisy media reports. Since both processes are normal, we have that:

$$\mathbb{E}_t(\pi_{i,t+1}|\psi_{v,t}) = \rho_t \pi_{i,t} + (1 - \rho_t) \bar{\psi}_t \quad (2)$$

Where  $\bar{\psi}_t = 1/V \sum_{v=1}^V \psi_{v,t}$ . Then, the mean of the distribution of the posterior conditional on the available information is equal to the inflation expectation, and arises as a weighted average of the mean of the prior

and the average of the noisy information obtained from the media. This weighting is associated with the relative importance that individual  $i$  assigns to her beliefs and to public information, such that a higher  $\rho_t$  implies a subject with certainty about her beliefs so she will strongly rely on them and will be little attentive to media information.

Solving the process we will get a function that defines the behaviour of our attention dynamic parameter:  $\rho_t = g(\sigma_\psi^2; \sigma_a^2; V)$ , where is expected that  $\partial\rho_t/\partial V < 0$ , the more information the less importance is given to the initial belief;  $\partial\rho_t/\partial\sigma_a^2 < 0$ , the greater the personal uncertainty the more people will seek public information, and  $\partial\rho_t/\partial\sigma_\psi^2 > 0$ , the greater the disagreement in the predictions of professionals, the less relevant they will be to the individual, and the greater the importance of their own beliefs.

Those relationships allow to define an equation of motion for the variable of interest ( $\rho_t$ ), which will form the State Equation (Transition of the State variable), in order to estimate its dynamics over time.

$$\rho_t = \gamma_1\rho_{t-1} + \sum_{i=1}^k \theta_i x_{i,t} + \eta_t$$

This dynamic has a certain persistence over time, which is why an AR(1) process is assumed<sup>3</sup>, and it is also determined by our variables of uncertainty ( $\sigma_a^2$ ), discrepancy ( $\sigma_\psi^2$ ) and amount of news ( $V$ ).

$$\rho_t = \gamma_1\rho_{t-1} + \theta_1 \frac{\sigma_\psi^2}{\sigma_a^2} + \theta_2 V_t + \eta_t \quad (3)$$

Where  $\eta_t \sim N(0, \sigma_\eta^2)$  and  $\rho_t \in [0, 1]$ , which takes value 1 when all the attention is put on one's own beliefs, and 0 when the beliefs are completely disregarded, taking total relevance from the news received.

Equation 3 allows the parameters to be updated  $\forall t$ ; in addition, expectations can be formed with partial information. The refinement proposed in Galará, 2021 introduce *subjective* indexes that refers to consumers' *economic humor*, assuming that they contain all other information about the expected economic performance (apart from professional expected inflation) in order to update personal beliefs in a given period.

The average inflation expectation at the national level will be the dependent variable that constitutes the *posterior* of the model  $E_t(\pi_{t+12})$ , and its variance for each month is the measure of uncertainty of the public ( $\sigma_a^2$ ); the inflation expectations of the professionals determine  $\bar{\psi}_t$  and their monthly variance ( $\sigma_\psi^2$ ) a measure of professionals' discrepancy; we also have the number of professional forecasters at each month, which give us  $V$ . Then the subjective indexes (ICC, ICG, CSI and ESI) are added to the different models to better specify the process.

### 3.1 The structural model

To extend the model I start stating an structural VAR version for the formation of inflation expectations ( $\pi_{t+12}^e$ ) given the available information set  $\omega_t$ , in aggregate terms:

$$[\pi_{t+12}^e | \omega_t] = \beta_\alpha \alpha_t + \beta_f f(\gamma_t | \kappa) + \varepsilon_t \quad (4)$$

Where  $\alpha_t$  (the anchorage) is the average *prior* belief about expected inflation in the population, the *core* of what people perceive and expect in the aggregate at the beginning of the period<sup>4</sup>. The aggregate or general perception factors ( $\gamma_t$ ) are defined as the updating parameters of the *anchorage*, they interact to process the available information in the period and adjust the initial belief. An important note is that the aggregate perception of the context is going to depend on the characteristics of the population ( $\kappa$ )<sup>5</sup>.

<sup>3</sup>The possibility of greater persistence was tested with an AR(2) process, but in this case higher order lags were not informative, and the explanatory variables lost all relevance since all the dynamics were explained by the agents' attention. The use of an AR(1) model is consistent with what Lamla and Sarferaz, 2012 proposed in their estimations.

<sup>4</sup>It is easy to declare that it could be equal to the expected inflation of the previous period,  $\alpha_t = [\pi_{t+11}^e | \omega_{t-1}]$

<sup>5</sup>i.e., the type of consumers who dominate the formation of expectations, either because they are the majority of people (in a herd behavior scheme) or because they are an exclusive group of insiders (leader-follower).

Finally, we need to add an exogenous disturbance proper to the aggregation process ( $\varepsilon_t$ ), resulting from model misspecification and unobserved factors that bias the general context perception.

Assuming that households are homogeneous, we can perform the analysis with aggregated data (survey averages) by equation 2:

$$\mathbb{E}_t(\pi_{t+12}|\psi_{v,t}) = \rho_t\pi_t + (1 - \rho_t)\bar{\psi}_t + \varepsilon_t \quad (5)$$

Where households define expectation based on initial beliefs, the new (unprocessed) information about inflation predicted by professionals and a stochastic component that adds volatility to the prediction. In a parallelism with the theoretical model in (4)  $\pi_t \equiv \alpha_t = \mathbb{E}_t(\pi_{t+11}|\psi_{v,t-1})$ , defined by the initial belief about inflation. On the other hand, the main contribution of the model in (4) is to reduce stochasticity ( $\varepsilon_t$ ) by incorporating the factors that define the households' aggregate perception, particularly those referring to the macroeconomic context, so  $\varepsilon_t = f(\gamma_t|\kappa) + \nu_t$ . At this point, equation (5) is reformulated as:

$$\mathbb{E}_t(\pi_{t+12}|\psi_{v,t}) = \rho_t\pi_t + (1 - \rho_t)\bar{\psi}_t + \phi_f f(\gamma_t|\kappa) + \nu_t \quad (6)$$

## 4 Outcomes

The state-space model set by 6 & 3 allows, first, to estimate by maximum likelihood the parameters that best fit the structural specification for inflation expectations. Then by Kalman filter, identify the path of realizations that best represent the dynamic parameter  $\rho_t$ . Before all this, a structural VAR give us the initial values needed for this set-up and some valuable information about the DGP of inflation expectation in the long-run.

Different models were tested following Equation 6 but with static parameters (structural), using the average (US) or the maximum (Argentina) of the professional expectations, and the subjective measures of macroeconomic perception<sup>6</sup>, in levels, in growth rate, interacting or as a compound variable called *MacroMood*. The most relevant outcomes for Argentina are summarize in table 5, where we see that model 4 is the better specified, with all coefficient significantly different from zero (with exception of  $\Delta ICG_t$ ) and a better likelihood than the one from the ARMA(2,2) model.

For the US we have (table 6) that the best model is the one that included the growth rate of *MacroMood* measure (an interaction between CSI and ESI) and, as in the Argentinian case, this model also surpass the AR(1) specification adding relevant information.

In both cases the explanatory variables are consistent with our main model, and with the expected signs. Previous expectations is the most relevant covariate taking the place of the prior; professional forecast are the external updating source; and the macro-perception elements are the inner updating source, negatively related to expected inflation (the better perception the lower the expected inflation).

### 4.1 A short note about causality

In order to estimate the VAR models consistently and optimally I ran different test to determine the lags order for all variables, being significant to work with only one lag. The one lag VAR for all variables concludes that for each of them only their own lags were relevant but not those of the other variables.

Granger causality tests indicate that the exogenous variables in  $t - 1$  are not predictors of the dependent variable in  $t$ . In the relationship between explanatory variables and inflation expectation we can assume that the latter will be explained by its previous value (prior) and by the contemporaneous values of the former (professionals' forecast and macro-perception).

Two facts can be recovered from this. First, the direction of causality between explanatory and the dependent variables. On one side, the expectation of professionals (better informed and with more sophisticated estimation methods than consumers) should not be affected by the public's expectation, at least not by the contemporaneous one. On the other hand, current perception of the economy and the political scenario

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<sup>6</sup>I tested multicollinearity among the explanatory variables with a regression of those metrics between each other, and get all variance inflation factors (VIF) close to 1, so there was no sign of it.



cannot be at all defined or conditioned by next year’s inflation expectation; however, causality does make sense in the inverse direction for both cases.

Second, the fact that historical values (*lags*) of the explanatory variables are not informative for the estimation and only ( $IE_{t-1}$ ) is could be associated to the fact that the inflation expectation of the previous period already contains all those information.

## 4.2 State-space results

The structural specification that will be used to estimate our models are:

$$\text{Argentina } IE_t = \rho_t IE_{t-1} + (1 - \rho_t) \max(\psi_t) + \phi_1 \Delta ICC_t + \phi_2 \Delta ICG_t + \nu_t \quad (7)$$

$$\text{USA } IE_t = \rho_t IE_{t-1} + (1 - \rho_t) \bar{\psi}_t + \phi_3 \Delta MacroMood_t + \nu_t \quad (8)$$

With the observed data from each country ( $y^T$ ) and a set of initial values (which are assigned based on the data and the parameters in Appendix A) it is possible to estimate by maximum likelihood and Kalman-filter the equations 7, 8 and 3 iteratively. A first time to find the parameters  $\Gamma \equiv (\phi, \sigma_\nu^2, \gamma_1, \theta_1, \theta_2, \sigma_\eta^2)$  that best fit the model; the second time taking them as given to estimate the path of the state variable such that:

$$\rho^T \equiv (\rho^T | \Gamma, y^T)$$

It should be noted that, in the model, the variable to be estimated is  $\rho_t$ , so all other values are constant and do not interact with it (in terms of their variances and covariances). Since the variables  $IE_t$  and  $\bar{\psi}_t | \max(\psi_t)$  do interact with the state variable, it is possible to suppress the need to work with the covariances of both variables by making a mathematical arrangement based on the structure of the model in 6, leaving:

$$IE_t^* = \rho_t IE_{t-1}^* + \phi_f f(\gamma_t | \kappa) + \nu_t \quad (9)$$

With  $IE_t^* = IE_t - \max(\psi_t)$  and  $IE_{t-1}^* = IE_{t-1} - \max(\psi_t)$  (or  $\bar{\psi}_t$  for the US); and  $f(\gamma_t | \kappa) = [\Delta ICG_t \quad \Delta ICC_t]$  (or  $[\Delta MacroMood_t]$  for the US). The results of the maximum likelihood estimation for our parameters of interest are summarize in Table 2. There we see that not all coefficients are relevant, but the ones from the structural equation have the proper sign for both countries, the same for the State Equation for Argentina, however, for the US they’re mainly non-significant, and there’s evidence that  $\rho_t$  behaves in general as a random walk with some relevance of the amount of available news. Overall the log likelihood is maximize at higher values than the ARMA models (Table 1) and the structural VAR summarized in Appendix A.

Table 2: State-Space model estimates

Country	Structural Equation (Observation)			State Equation (Transition)				Log-lik
	$\phi_1   \phi_3$	$\phi_2$	$\sigma_\nu$	$\gamma_1$	$\theta_1$	$\theta_2$	$\sigma_\eta$	
Argentina	-0.240 (0.0340)	-0.015 (0.0180)	1.816 (0.0893)	0.667 (0.0446)	0.441 (0.1812)	0.005 (0.0010)	0.134 (0.2069)	-385.12
US	-0.005 (0.0041)		0.129 (0.1251)	0.210 (0.1440)	-0.155 (0.9088)	0.017 (0.0038)	0.1512 (0.1496)	20.66

*Std.dev.* in parentheses

## 4.3 Historical analysis

With Kalman-filter I recover the trajectory of the latent variable  $\rho_t$ , the attention factor, and its variance, the speed of updating factor, and plotted them in Figures 3 and 4, together with some relevant information breaks for each country and the world (See Appendix B). It can be appreciated that they are related with significant changes on the dynamics of our variables of interest.

For Argentina, the first half of our studied period is marked by a fuzzy behavior of attention, varying rapidly around a 70% relevance of households’ beliefs, exhibiting the great uncertainty that governs Argentinian economy in general, and inflation in particular, during those years. We see that this uncertainty begins a

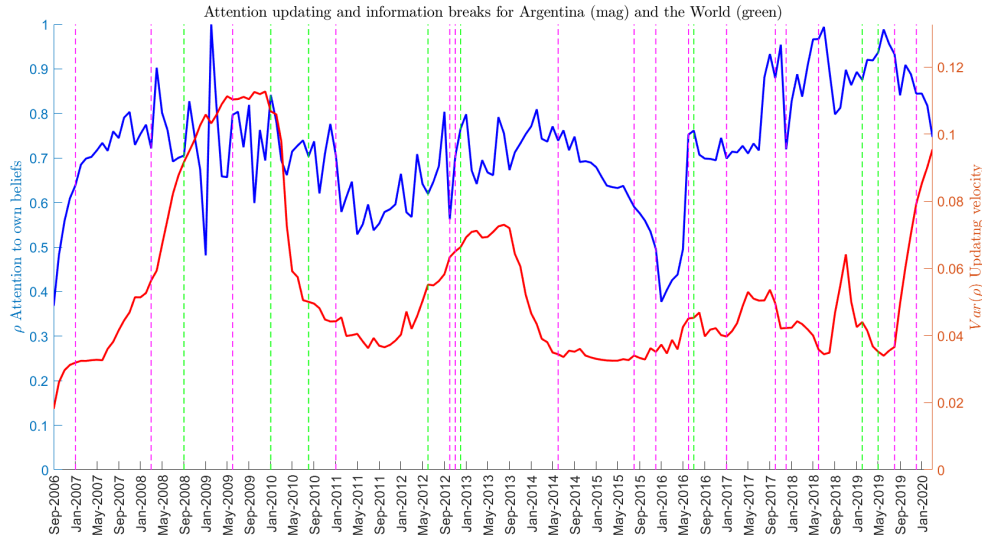


Figure 3: Argentina: Attention updating and information breaks

few months earlier than the Great Recession (GR), at the end of March of 2008 when an inner crisis emerge with agricultural producers taking force measures due to a tax increase on commodity exports, carrying out a general strike and blocking roads throughout the country, generating a climate of general discontent with the national government. In this period we see that uncertainty rises even more when the effects of the GR hit the world. This is the period of the largest variance of  $\rho$ , which last till the beginning of the second half of 2009, coinciding with both the end of GR and the legislative elections in Argentina, in which the ruling party loses their majority in the National Congress.

The rest of this first period was marked by a government credibility crisis, first due to doubts around manipulation of official CPI after inflation started to accelerate as a consequence of populist policies; we see this effect clearly in the important fall of  $\rho$  after Jan-11, when the National Congress started to public their own CPI figures, so people move to search outside information about the evolution of inflation, setting a period of almost a year and a half with low attention and low variance of it. This last till the end of 2012, when the Central Government prohibit parallel publications of CPI ciphers and their derivatives (like professional forecast), starting an other period of significant volatility, that only worsen and finish when Argentina enters into selective default at Jun-14, due to a ruling by Judge Thomas Griesa withholding Argentine government payments to creditors of restructured bonds, considering that debt payments to *Hold-out* holders (*vulture funds*) should also be honored. This changes the whole macroeconomic structure of Argentina, so after that we see the attention falls to its minimum, as a signal that own beliefs were no longer representative of the current national context. The fall accelerated after mid-term presidential elections in 2015 and the effective change of government with the beginning of Mauricio Macri's presidency.

The second half of our Argentinian historical overview started with this new administration, and marked a huge recovery of the attention measure only after the new administration announce a revision of CPI measurement in Jun-16, which enhance even more at the second half of 2017 when Macri apply his main Economic Reforms which aimed to reduce inflation, attract foreign investment, and address fiscal imbalances<sup>7</sup>, and after his party gain more power in the National Congress in Oct-17, which strengthened their economic agenda.

However, this period of relative calm ends after the central administration announce (with lots of controversy) an important change in their inflation and devaluation program which weakened public support, and that get even worse when the president announced that Argentina was not able to sustain their fiscal and financial agenda and needed an Stand-By credit from IMF in Jun-18. After that, uncertainty risen and we

<sup>7</sup>These reforms included removing currency controls, cutting subsidies, and implementing austerity measures.

see that households' confidence on their own beliefs started to fall searching fast for external information sources when every signal along the year 2019 anticipates that there will be a change of administration in line with the party that rules during the first half of our series.

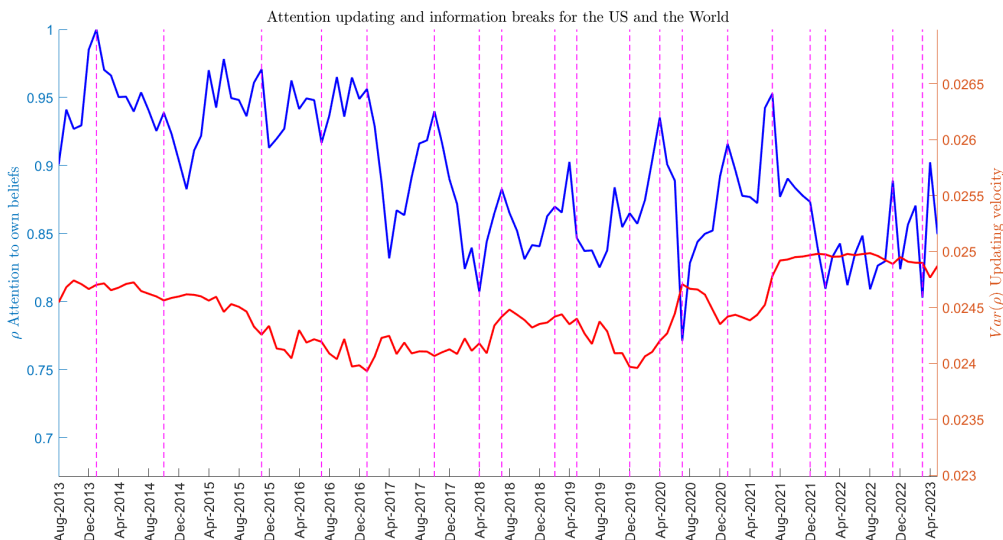


Figure 4: US: Attention updating and information breaks

This same historical-economic analysis can be performed for the US. We can see in Figure 4, for example, that American households' are better informed than Argentinian ones, so  $\rho$  moves around a 85-90% relevance of own beliefs, with much less significant volatility. Even though our model isn't too strong for the US, it allows us to track relevant information breaks with the dynamics of attention and its volatility, with peaks and troughs that match almost perfectly those national and international events.

Regime switching, like the beginning of Trump's administration (Jan-17) or COVID-19 pandemic outbreak (Apr-20), and of its most important variants (Delta and Omicron in Jul-21 and Dec-21 respectively), were followed by a drastic fall of our attention measure. The presence of international conflicts like Charlie Hebdo Attack (Jan-15), Brexit (Jul-16) or Ukrainian war (Feb-22), are followed by short periods of consecutive peaks and troughs of almost the same size, indicating that households are adjusting their beliefs. On the other hand, events that affects inner credibility, like Cambridge-Analytica scandal (Apr-18) and Silicon Valley Bank collapse (Mar-23), or that recover the macroeconomic context, like anti-COVID measures in Jul-20, makes agents strongly support their own beliefs, in the first two cases disregarding external information due to lack of credibility or excess uncertainty, and in the second case recovering from previous falls to the original levels of confidence.

To complement the analysis, I also preset some tables summarizing how the attention variable and the updating speed correlates with the three selected uncertainty measures: World Uncertainty index from IMF (WUI), the country-specific uncertainty index (Arg-UI or FED US-UI) and our Google-based uncertainty measure (Google-Arg and Google-US). For this correlation I focused both on the whole series joint dynamics and on the dynamics on specific information breaks related to relevant events in our countries of interest.

Table 3 (Panel A) shows that, in general, the attention measure increases with greater global uncertainty and with our Google-based<sup>8</sup> measure, relation that is stronger when focusing only on Argentinian information breaks (Panel B), this support the hypotheses that households search for more information (consistent with our Google measure) during those points to strengthen their beliefs. On the other hand, when people

<sup>8</sup>WUI is positively correlated with Arg-UI ( $Corr - Coeff = 0.177$ ) and Google-Arg (0.204), however, both Argentinian uncertainty measures show no correlation (0.014), this is because of methodological differences, while the former tracks-down Twits with key-words related to the concept *uncertainty*, our Google Trend measure focus on the search of key words related to economic and political uncertainty specific for the country, while the first measure directly the lack of information, the second measure the search for new information and learning about the current context.

claim that they are *suffering from uncertainty* in social media (Arg-UI), correlation is highly positive with updating speed ( $Var(\rho)$ ), also (but weaker) for Google-Arg and WUI, consistent with what is expected.

Table 3: Argentina: Attention and updating speed correlation with uncertainty

Panel A: General data			Panel B: Specific points		
Corr Coeff	$\rho_t$	$Var(\rho_t)$	Corr Coeff	$\rho_t$	$Var(\rho_t)$
<b>WUI</b>	0.274	-0.097	<b>WUI</b>	0.337	0.127
<b>Arg-UI</b>	0.037	0.285	<b>Arg-UI</b>	-0.008	0.715
<b>Google-Arg</b>	0.301	0.027	<b>Google-Arg</b>	0.526	0.261

For the US (Table 4), we can appreciate an inverse logic, which is consistent with what would be expected *a priori*, a strong-negative relationship (specially with Google-US<sup>9</sup>) between uncertainty and attention. In the specific turning points (Panel B) there is almost no correlation between updating speed and US specific uncertainty index<sup>10</sup>.

Table 4: US: Attention and updating speed correlation with uncertainty

Panel A: General data			Panel B: Specific pints		
Corr Coeff	$\rho_t$	$Var(\rho_t)$	Corr Coeff	$\rho_t$	$Var(\rho_t)$
<b>WUI</b>	-0.186	-0.174	<b>WUI</b>	0.032	-0.400
<b>FED US-UI</b>	-0.359	-0.024	<b>FED US-UI</b>	-0.213	-0.095
<b>Google-US</b>	-0.629	0.264	<b>Google-US</b>	-0.646	-0.091

## 5 Conclusions

Beyond the evidence supporting that inflation associated phenomena can be modeled sufficiently well with ARMA process, at least for households in Argentina and the US, we see that there are gains in extending the specification, including new variables related to each period information. This allows us not only to better represent the phenomenon and predict its results more accurately, but also to better understand it by following the evolution of its components, obtaining measures of people’s uncertainty, their mechanisms for processing the available information and their position towards it, their confidence in their beliefs, and the impact of certain relevant news shocks on these expectations.

The importance of understanding this process and having methods to anticipate it is not trivial, since these expectations directly affects macroeconomic outcomes of utmost importance, such as short-term consumption and savings decisions, and their transmission through channels such as labor supply and investment. Additionally, we observe that these new measures derived from the state-space model, attention and the speed of belief updating, correlate with uncertainty, and that their dynamics are defined not only by the inflationary context but also by idiosyncratic components of the population and the quality of available information.

A few years ago, inflation was considered a problem only for some underdeveloped countries, nowadays public policies that sought to reduce the recessionary effects of the COVID-19 pandemic have brought it back to households’ daily decisions, turning it into a main macroeconomic issue for many governments. Independent if inflation is or not a problem for certain countries, the application of a (well micro-founded) model of aggregate inflation expectations makes it possible to summarize numerous factors of the behaviour of consumer agents, even considering biases and rationality breaks.

<sup>9</sup>Our Google-based index is positively correlated with both the FED US-UI (0.281) and the WUI (0.244).

<sup>10</sup>The updating speed is negatively correlated with WUI, however there is no empirical interpretation of this outcome.

## References

- Atkeson, A., Ohanian, L. E., et al. (2001). Are phillips curves useful for forecasting inflation? *Federal Reserve bank of Minneapolis quarterly review*, 25(1), 2–11.
- Canova, F. (2007). G-7 inflation forecasts: Random walk, phillips curve or what else? *Macroeconomic Dynamics*, 11(1), 1–30.
- Ferroni, F., & Canova, F. (2021). A hitchhiker’s guide to empirical macro models.
- Galará, I. (2021). Miopes y pesimistas: ¿cómo forman sus expectativas de inflación los argentinos? revisión empírica de un modelo teórico agregado de expectativas con sesgos de información. *Working paper*, 2021, 37.
- Lamla, M. J., & Sarferaz, S. (2012). Updating inflation expectations [KOF working papers No. 301]. <https://ssrn.com/abstract=2030270%20or%20http://dx.doi.org/10.2139/ssrn.2030270>
- Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. *Journal of monetary economics*, 44(2), 293–335.
- Weber, M. (2022). Subjective inflation expectations of households. *Business Economics*, 1–5.

## A Structural VARs

Table 5: Structural VAR model for Argentina

Variables	(1)	(2)	(3)	(4)
$\psi_t$	0.228 (0.0407)			
$ICG_t$	-3.287 (0.624)	-2.901 (0.528)	-0.715 (0.523)	
$ICC_t$	-0.330 (0.0572)	-0.320 (0.052)	-0.122 (0.0377)	
$max(\psi_t)$		0.214 (0.0352)	0.0484 (0.0205)	0.0579 (0.0198)
$IE_{t-1}$			0.710 (0.0454)	0.717 (0.0459)
$\Delta ICG_t$				-0.0209 (0.0189)
$\Delta ICC_t$				-0.0213 (0.0340)
$\beta_0$	48.33 (2.721)	45.63 (2.650)	14.84 (2.502)	3.377 (0.918)
Observations	163	163	162	162
$Log - Lik$	-463.6	-454.2	-373.7	-353.8

Robust standard errors in parentheses

Table 6: Structural VAR model for USA

Variables	(1)	(2)	(3)
$\psi_t$	0.0755 (0.103)	0.00784 (0.0983)	0.0190 (0.0951)
$ESI_t$	-0.00138 (0.0027)		
$CSI_t$	0.00483 (0.0018)		
$IE_{t-1}$	0.970 (0.0521)	1.025 (0.0438)	0.969 (0.0359)
$MacroMood_t$		0.00575 (0.00306)	
$\Delta MacroMood_t$			-0.0139 (0.00404)
$\beta_0$	-0.452 (0.421)	-0.664 (0.412)	0.0664 (0.129)
Observations	118	118	118
$Log - Lik$	10.65	8.895	12.79

Robust standard errors in parentheses

## B Historic highlights

### Argentina

Period	Event
Jan-07	The national institute of statistic (INDEC) is intervened by the central government
Mar-08	Inner crisis with the agricultural sector (3 months of protests)
Jun-09	Legislative elections eliminate Congress majority to the ruling party
Jan-11	The opposing parties at the National Congress start publishing a parallel CPI
Oct-12	All parallel CPI publication are prohibited (with exception of the Congress CPI)
nov-12	Judge Griesa states that Argentina must honor its debt with hold-outs
Jun-14	Hold-out's crisis after NY court rejects Argentina's claim
Aug-15	Preliminary elections in 2015
Dec-15	Mauricio Macri starts his presidency
Jun-16	A CPI revision is informed, to correct miss-information after years of statistics intervention
Jan-17	New CPI is published
Oct-17	National Congress elections strengthens the central administration power
Dec-17	Inflation target changes drastically, public loose reference and government credibility
Jun-18	Government announce a Stand-By credit with IMF
Aug-19	Preliminary elections in 2019
Dec-19	Alberto Fernandez starts his presidency
Apr-20	COVID-19 pandemic settles in Argentina
Aug-21	Inner political crisis

## US/World

Period	Event
Sep-08	Great Recession outbreak
Jun-09	Great Recession "ends"
Jan-10	Great Financial Crisis policies to "recover" after the GR
Aug-10	Great Financial Crisis and debt risk in the EU (Portugal and Greece)
Jun-12	EU Fiscal Compact, to enhance fiscal discipline among Eurozone member states
Dec-12	US fiscal cliff crisis
Jan-14	Obamacare & FED's reduction on bond buying program
Oct-14	Ebola outbreaks & USA strikes ISIS
Nov-15	Paris terrorist attack
Jul-16	Brexit
Jan-17	Donald Trump presidency starts
Oct-17	#MeeToo movement — Catalonia's Independence referendum
Apr-18	US & China Trade tensions (escalate). US airstrikes in Syria. Facebook-Cambridge Analytica data scandal
Jul-18	International conflict: US vs China and Russia
Feb-19	US-Mexico border tensions. Trump order to build a wall
May-19	Trade tensions 2
Dec-19	Impeachment proceedings against President Donald Trump began
Apr-20	COVID outbreaks as a pandemic
Jul-20	Intensified anti-COVID measures
Jan-21	Joe Biden presidency — Capitol riot
Jul-21	COVID Delta variant & US bill negotiation
Dec-21	COVID Omicron variant
Feb-22	Ukrainian war
Nov-22	Cost of living crisis and US monetary policy strengthens
Mar-23	Collapse of Silicon Valley Bank