Department of Political Economy

King's College London

Dissertation Cover Sheet

Programme:	BSc Hons Philosophy, Politics, and Economics
Module code:	6SSPP352
Candidate number:	AF01169
Title of your dissertation:	*Online Social Amplification and Consumer Inflation Expectations:* *Evidence from Brazil (2015–2023)*
Supervisor name:	Federica Carugati
Word count*:	7,848

May 9, 2025

Abstract

This undergraduate dissertation offers insight into inflation expectations. I assess the role of online media in affecting consumer inflation expectations in Brazil, using eight years of data, 400,000 observations and a Vectorauto Regression with Exogenous Controls. I find that online media tone in Brazil impacts consumer inflation expectations with a magnitude of 3.5 percentage points over eight months. At the end of the paper I offer possible policy insights and speculations.

Acknowledgements

As I conclude the writing of this dissertation, I also mark the end of my undergraduate studies and what has been one of the most sincere and meaningful experiences of my life. First and foremost, I thank my family for the opportunity to attend this degree. The importance of this education, and the way it has shaped the way I see and take on the world, will always be something I am grateful for. I also want to thank Dr. Federica Carugatti for her continued support for the past two years as my lecturer, mentor, and supervisor. Your guidance has taught me the invaluable skill of constructing meaningful and impactful arguments and the importance of intentionality. I thank Camille Bacha for helping me take on what was for me a new world of Brazil; Anna Carlina for her trust, effort, and time sharing her expertise; and Nour Shamala for her moral support throughout the many sleep-deprived nights it took to write this dissertation. Finally, I share my gratitude for my people—the Egyptian people—who initially motivated this topic. In particular, the 2022 Egyptian inflationary spike which cut almost 50% of household real income. The lessons derived from this dissertation are dedicated to those suffering from the pernicious effects of inflation.

Contents

List of Tables

List of Figures

List of Abbreviations

CIE Consumer Inflation Expectations

IE Inflation Expectations

CCI Consumer Confidence Index

GDELT Global Database for Events, Language & Tone

PPP Purchasing Power Parity

IMF International Monetary Fund

FGV Fundação Getulio Vargas

V–DEM Varieties of Democracy

VAR Vector Autoregression

VARX Vector Autoregression with Exogenous Controls

AIC Akaike Information Criterion

FPE Final Prediction Error

HQIC Hannan–Quinn Information Criterion

SBIC Schwarz (Bayesian) Information Criterion

OECD Organisation for Economic Co-operation and Development

IRF Impulse Response Function

API Application Programming Interface

ECB European Central Bank

Introduction

According to the International Monetary Fund, as of 2022, global inflation rates have been the highest since the mid-1990s (Ha et al), and pose the 7th largest threat to global security (WEF, 2024). Coupled with the declining effectiveness of inflation management tools, these high inflation rates pose significant threats to the stability of economies and the welfare of their residents (Eden, 2016). Previously, the main tools used by governments have mainly involved the manipulation of interest rates with the objective of incentivising or disincentivising spending, hence, curbing or pushing demand. However, the effectiveness of these policies has seen a steady decline, prompting concern in the literature surrounding inflation, with many academics calling for a further investigation of inflationary mechanisms (see Coibion et al, 2020; Bryan et al, 2015). This dissertation aims to contribute to this assessment by studying the effect of online media tone on inflationary mechanisms.

Historically, central banks' efforts have centred around demand and supply manipulations, and inflation expectations have gone somewhat underattended (Adrian, 2023). While the negligence of inflation expectations is somewhat warranted for some countries, such as OECD countries, whose inflation is almost entirely explained by global supply and demand shocks (Parker, 2018; Ha, 2024). These shocks only explain 10-20% of inflation in non-OECD countries, yet again raising concerns regarding inflationary mechanisms (Ha, 2024). Subsequently, research efforts have been made to clarify and quantify whether inflation expectations are, in fact, economically relevant for any future policy discussions. To which a literary common consensus has been reached that– yes, expectations matter because: one, they affect household consumption and saving habits. Two, they shape firm price and wage setting benchmarks. As a result, unanchored expectations create volatile outcomes and reinforce inflation, thus suggesting its potential as a policy tool (see Coibion et al, 2020; Bryan et al, 2015).

Having established the relevance of inflation expectations for economic stability, the next set of concerns begins to take form. First, whether inflation expectations should be used to guide policy tools, and how. Moreover, preceding both, whether our understanding of inflation expectations functioning is even sufficient. While we have some understanding of how expectations are formed, understanding is limited (see ECB, 2024; EUCPR, 2024; Coibion et al, 2020); however takes the following form (see Ranyard et al, 2008): consumer expectations are a function of inputs– prices and forecasts, subject to multipliers– social amplification, personal income, and attitudes. At this stage, I clarify that from the two forms of expectations, consumer and firm, this essay chooses to focus on consumer expectations, given that: one, the spatial limits of this essay only appropriately warrant the exploration

of one aspect. Two, the research question, which will be presented, while applicable to firm expectations, better aligns with consumer expectations.

Further refining the scope of this essay, of the components of inflation expectations (prices, forecasts, income, attitudes and social amplification), this dissertation chooses to explore social amplification. Kasperson et al define social amplification as the amplified signalling of a given risk arising from public perception, which reflects "intuitive biases and economic interests and [...] cultural values" (P.178, 1988). The complexities of social amplification suggest it as an interesting component of inflation expectations. Moreover, with the rise of digital and internet use, a parallel online amplification sphere has also developed. This online amplification sphere, often realised through digital news outlets and social media, provides an even more complex topic, additionally subject to global inputs and digital algorithms.

Thus, so far, I have explained how rising inflation rates and waning inflationary tools have prompted discussions on the possible relevance of inflation expectations. Subsequently, I share the results that expectations do, in fact, matter for overall economic outcomes. However, prior to the use of expectations within policy, a better understanding of its mechanisms is necessary (per Coibion et al, 2020). From the components of inflation expectations, I choose to test whether online social amplification is relevant to policy discussion. I arrive at the question: Does online social amplification affect inflation expectations? Refined to:

Do variations in the economic sentiment of online social amplification affect inflation expectations?

The refinement narrows down the aspects of the online social sphere to only economic ones. This follows from US Federal Reserve Board member Jeremy Rudd's findings that consumers only alter expectations when confronted with direct information on inflation or prices (2021). Therefore, including variations in other topics is unnecessary, thus justifying this refinement. For my empirical analysis, I use Brazil as my case study for a few key reasons: First, it has had volatile inflation in the past ten years with more than 10% variations, enabling potential for testing (IMF, 2024). Second, 89% of its population has access to the internet, meaning most civilians are exposed to online spheres (ICT, 2024). Third and most importantly, it offers a reputable independent consumer expectation survey, a proxy widely used for consumer inflation expectations (see FGV, 2020).

Subsequently, for the empirical portion of the essay, I use the Global Database for Events, Language and Tone (GDELT) to proxy online economic sentiment. The database provides open access to 3.5 billion datapoints tracking global media topics and tone. I extracted

data on 400,000 news articles on economics in Portuguese, on Brazilian domains, across ten years, alongside their tone rating, hence compiling an original dataset on Brazilian media tone. As for consumer inflation expectations, I use Fundação Getulio Vargas's (FGV) consumer expectations survey available at a monthly frequency. To summarise, I test the effect of GDELT tone changes on FGV expectations. Using these two main variables, I run a Vector AutoRegressive model with exogenous constraints (VARX). This model is particularly useful because it captures the dynamic temporal relationship between both variables. Meaning that the model not only captures the contemporaneous effects but also its lagged effects. Put into context, it acknowledges how consumers don't instantaneously update expectations for every signal received. Rather, the model takes into account the temporal quasi-linearity of expectations and how tone signals may stack over time. Equally important, the model also accounts for how expectations may hold over time, giving insight into how long the effect of tone variations lasts. Additionally, the constrained variation enables the inclusion of necessary controls such as political stability, which possibly affect expectations and perceptions of economic security. Finally, the VARX framework is well-established in the inflation-expectations literature, lending empirical credibility to its adoption in this dissertation (see Becmann, 2020; Barnett, 2010; Istrefi & Anamaria, 2014).

Running this model, I find that GDELT (online media tone) has almost no instantaneous impact on CCI (consumer inflation expectations), however, its effect rises to a 3.5 percentage point impact by the second month. Gradually, it begins to fall to baseline at the lower bound after eight months. Moreover, I also find that CCI carries strong inertia, with former expectations having a lasting six-month effect on current expectations. All findings are significant at 10%, 5%, and 1% significance levels. However, the model holds the following limitations: The compilation of GDELT data is somewhat reductive, the frequency of the exogenous controls is low, and the true exogeneity of the exogenous controls is debatable. Nevertheless, the model is more than sufficiently significant to indicate: online media does matter for consumer inflation expectations.

While the singular case study of Brazil also suggests the questionable generalisability of my results. Nonetheless, I would argue that consumer expectation mechanisms are relatively uniform, subject to variations in central bank effectiveness and reputability, inflation environment, economic stability, and real income perceptions. Therefore, most emerging markets would likely satisfy these generalisability conditions. The IMF makes similar assumptions and generalisations (Albrizio & Bluedorn, 2023). Moreover, in this dissertation, I offer two novel contributions: An original panel data set on Brazilian inflation expectations. Additionally, and more notably, I offer what I believe is likely one of, or the only, works of empirical analysis on the effects of online media tone on consumer inflation expectations. With more

certainty, I believe this is the only one of its type conducted on an emerging economy.

The remainder of the essay will be structured as follows: One, a more detailed literature review on how expectations translate into economic outcomes, how expectations affect the overall economy, and finally, how expectations are formed. Two, a Hypothesis & Limitations section, where I provide a more concrete overview of the objectives of this dissertation. Three, a Methodology and Model section, where I will justify my variables, proxies, and engage with the econometric model and acknowledge the research's limitations. Fourth, I share the results from my model, with additional considerations of model limitations. Five, a Takeaway section where I highlight the findings' relevance and applications. Sixth, a policy analysis section offering three different lenses of analysis. Finally, I provide a conclusion and appendix.

Note: For the remainder of the essay, I abbreviate Consumer Inflation Expectations to CIE, and Inflation Expectations to IE.

0.1 Literature Review

Having explained the relevance of CIE, this literature review aims to take a more granular approach regarding existing literature on how CIE translate into tangible economic outcomes, how expectations are formed, assumptions regarding consumer attitudes, and CIE in the sphere of policy. Furthermore, I show that the motives of this dissertation are in line with relevant literature. Additionally, I clarify how I aim to contribute to our understanding of social amplification in the CIE sphere.

0.1.1 Inflation expectations and economic outcomes

As previously mentioned, consumer expectations primarily translate into economic outcomes via saving and spending channels. This rationale is often formalised using the consumption-saving Euler's equation below:

$$c_t \;=\; E_t c_{t+1} \;-\; \sigma\Big[\, i_t - E_t \pi_{t+1} \Big] \;=\; E_t c_\infty \;-\; \sigma \sum_{j=0}^{\infty} E_t (i_{t+j} - \pi_{t+1+j})$$

This formalisation suggests that long-term consumption c_t is dictated by the expected current and future interest rates latex $(i_t - E_t \pi_{t+1})$ where an increase in perceived inflation

rates $E_t\pi_{t+1}$ offsets the payoff of interest rates, therefore reducing the incentive to save. In simpler words, ceteris paribus, if inflation rises, real interest falls, hence, the incentive to save decreases given a decrease in purchasing power. A significant amount of literature has verified these effects successfully: For example, D'Acunto, Huang, and Weber exploit the German 2005 3% VAT increase announcement for a difference in difference model, where they tested how household spending changed before and after the announcement (2016). Their results showed a 4pp increase in spending by households, ergo, aligning with Euler's equation– that when confronted with expectations of increasing costs, spending rises. These findings are also consistent with Ichui and Nishiguchi's findings from Japan (2013), and Duca et al (2018), who used pooling data from seventeen European countries and found consistent correlations between inflation and consumption. Similarly, Vellekoop and Wiederholt use a comprehensive household expectations survey for Dutch households and national household income data to calculate yearly variations in saving and spending (2019). They find that for every percentage point change in expectations, households average 250 euros less in savings.

However, opinions are not entirely uniform. Coibion et al challenge the generalisability of these findings in a controlled trial where a treatment group was provided with information that skewed their inflation perceptions relative to the control group (2020). They found that while rises in inflation perception slightly increased spending on non-durable goods, it significantly decreased spending on durable goods. Accordingly, the high inflation negatively impacted the subjects' perceptions of real income, resulting in a temporary offset of large purchases. As a result, overall consumption declined, therefore, opposing Euler's equation and the previous findings. Nevertheless, while the consensus regarding the exact movement of consumption and saving is not absolute, the literature clearly shows that variations in expectations result in real economic changes. These findings are particularly necessary for the relevance of this paper, given that the effect of online social amplification of CIE is only relevant if CIE translates into some economic outcome. Finally, I do note that findings are mostly limited to developed economies. This is likely due to a lack of comprehensive consumer expectation surveys in emerging markets, however, I compensate for this in the next section.

0.1.2 The magnitude of inflation expectations:

Having established that CIE results in tangible economic outcomes, logically, the next question that arises is whether the IE-motivated variations in consumption and saving are signif-

icant enough to impact overall inflation. Or, put differently, whether these CIE effects are strong enough to matter for policy. In short, yes. According to the International Monetary Fund IMF, CIE is transmitted to overall inflation through two main channels, pass-through rates, and inflation inertia; otherwise known as soft/harsh landings (Albrizio & Bluedorn, 2023).

Pass-through rates refer to the proportion of a driving inflationary shock that is additionally realised through IE. For example, if a consumer observes a 1% drive in an inflationary shock from some global occurrence, such as the Russia-Ukraine war. If in response, the consumer aggressively updates their consumption and saving habits, the additional inflation arising from their response would be denoted by the pass-through rate. Such that, for example, ceteris paribus, for every 1% change in an initial driver shock, a 0.7 transmission rate would result in a total 1.7% change in the final Consumer Price Index CPI. This relationship is more formally represented by the linear inflation-pass-through equation below.

$$\pi_t = \alpha + \phi\,\pi_t^e + \mathbf{X}_t'\boldsymbol{\gamma} + \varepsilon_t, \tag{1}$$

π_t	Dependent variable: actual inflation, CPI or Producer Price Index (PPI)
α	A constant given by the baseline inflation when CIE and other controls are zero
π_t^e	Consumer inflation expectations at time t.
ϕ	Pass-through coefficient linking expectations to realised inflation.
$\mathbf{X}_t$	A vector of all control variables, such as price, demand, and exchange rate shocks
$\boldsymbol{\gamma}$	A corresponding set of economic sensitivity coefficients for every X variable $\mathbf{X}_t$.
ε_t	Error term.

According to the IMF, pass-through rates for developed economies average at about 0.8, and 0.4 for emerging economies (Albrizio & Bluedorn, 2023. Therefore, indicating that the overall economic effect of CIE is certainly relevant via pass-through channels. Put into perspective, in the case of Brazil's 2022 12% inflation hike, one could make the vague assumption that at a 0.4 emerging economy pass-through rate contributed 4.8% of the overall 12% rate (2023). While this assumption is extremely fragile and not conclusive by any means, it is a plausible indicator of the relevance of CIE for overall economic outcomes.

The second CIE channel is inflation inertia, sometimes called inflationary lags or sticky inflation. It explains how differences in consumer behaviour shape how long the effect of an

inflationary shock may last. If consumers are backwards-looking, inflation inertia is high, and past values significantly affect current perceptions. If they are forward-looking, inertia is low, and past values weakly affect current perceptions. These variations in inertia are what likely explain the 0.4 pass-through effect difference between developed and emerging economies. Assuming that consumer expectations in developed economies are grounded, consumers react accordingly to any given change in inflation or Central Bank announcement. Expectations move closely to contemporary changes. On the other hand, in emerging markets where information on inflation prospects tends to be scarce, and central bank communications are unclear or lack credibility, consumers' CIE become ungrounded and dependent on past experiences. As a result, current expectations are more significantly weighted by past experiences. Hence, pass-through is less reactive to contemporary changes, however, it carries significant inertia.

With regards to policy, high-inertia inflation poses stark challenges. If IEs are less responsive to contemporary signals and more heavily weighted towards past experiences, any attempt by central banks to ground CIE is then often met with irresponsiveness. In the case of Brazil, this challenge isn't unfamiliar; from 1970 to 1984, Brazil faced severe inflation of more than 100%, a result of strong inertia lasting almost 14 years (Bresser-Pereira, 2023). Eventually, economists froze prices nationwide, before eventually switching to a new currency– an event that would showcase the detrimental potential of CIE and strong inertia (Bresser-Pereira, 2023).

0.1.3 Formation of CIE:

Having illustrated the literature around CIE and the importance of it for overall economic stability, this subsection shifts to a more microeconomic literature overview on the specific inputs that shape IE. Subsequently, from this microeconomic scope, I aim to illustrate where online social amplification falls in relevance to other CIE inputs. To summarise the main literary consensus on CIE inputs, I use Ranyard et al.'s model for consumer socio-economic environment (2008). From this model, CIE can be understood as a function of three sets of inputs, the first and most studied being price signals. This refers to how consumers utilise available heuristics, such as, and mainly price changes from commonly purchased items, to gauge inflation. Ranyard et al suggest that price signal perceptions are affected by four aspects: frequency of purchase, recency of purchase, size of price change, and the direction of price change (p.385, 2008). For example, if the price of cigarettes were to rise,

regular smokers would likely assume an increase in inflation rates, however, a non-smoker's expectations would likely be unaffected. Other examples include gas and transport prices, all routine expenses that act as bases from which consumers assess price changes. Additionally, while CIE will differ based on price changes in familiar items, income also significantly skews perceptions. Fischer (2008, p. 372) argued that inflation is an issue of a decrease in perceived well-being. Thus, lower-income individuals are and feel more affected by price changes than higher-income individuals. In a questionnaire-based research, Bates and Gabor (1986) ask participants to guess prices from a menu of common items. They found that participants grossly overestimated inflation by 12.8% per annum, with lower-income participants showing stronger overestimating tendencies, confirming the prior statement.

The final main component is social amplification, or more specifically, the social amplification of risk (Pidgeon et al, 2003). According to Kasperson et al (1988), "amplification denotes the process of intensifying or attenuating signals during the transmission of information" (p. 180). Additionally, risk amplification tends to be extremely biased and asymmetric in risk vocalisation. These findings were confirmed by Soroka (2006), who used an autoregressive distributed lag model of UK macro indicators, the author successfully showing the media's reporting bias towards negative events. Finally, highlighting the effects of social amplification was Federal Reserve Board member Jeremy Rudd who suggested that consumers were so sensitive to any form of social amplification that the best solution was to completely remove the thought of economic status from consumer thought (2022).

Overall, this literature review has followed a series of topics relevant to the topic of online social amplification. I have started by reviewing the literature illustrating that CIE does, in fact, affect consumer behaviour through saving and consumption channels. In the following section, I highlighted key findings from the IMF that these variations in savings and consumption manifested in the macroeconomy via pass-through and inflation inertia channels. I show that these channels provide viable threats for macroeconomic stability, with pass-through rates potentially doubling overall inflation and inertias maintaining these effects for up to 14 years in the case of Brazil. Having shown the importance of IE, I provided an overview of how CIE formation is mostly dependent on price signals, well-being perceptions, and social amplification.

Despite these clear findings that indicate social amplification as a component of CIE the literature falls short of exploring the digital sphere and its possible increasing potential in perpetuating and contributing to social amplification. With the rise of chronic phone usage and addiction, the online sphere presents significant potential for impacting CIE through increased exposure to social amplification. As of the writing of this essay, 60% of the global population is active on the internet, with a 2.6% rise every year (Datareportal, N/A). Screen

time statistics show a global 6 hours and 40 minutes average, with Brazil at an average of 9 hours and 9 minutes, and South Africa reaching 9 hours and 37 minutes. Every year, this average increases by 30 minutes, and has been since 2013 (Duarte, 2025). Moreover, internet users are not only chronically online, but constantly unknowingly exposed to false information (Redline, N/A). While some research has explored the relationship between the frequency of inflation-related media articles and consumer CIE (see Coibion, 2019; Lamla & Lien, 2008), online media and internet algorithms remain underexplored.

0.2 Hypothesis and Limitations

Subsequently, this essay aims to contribute to the exploration and understanding of the growing online social amplification sphere and its impact on CIE. As mentioned, there are multiple mechanisms through which CIE may become influenced by the internet. More detailed examples include: digital misinformation, online media reporting frequency, online media reporting tone, online algorithms, large-scale social groups, social media, and particularly platforms like X (formerly Twitter) and Reddit, often used for discussions with algorithms that support significant social outreach.

Ideally, this essay would have explored social amplification through social media platforms like X, given its large user base, discourse analysis potential, the ability to track likes, comments, retweets, and finally its Application Programming Interface (API). These APIs have been widely used by academics for multiple purposes, ranging from misinformation research, data science, social media studies and more. According to Cornell University, as of 2006, Twitter/X APIs had enabled a total of "27,453 studies [...] published in 7,432 publication venues, with 1,303,142 citations, across 14 disciplines." (Murtfeldt, 2024). However, since February 2023, CEO Elon Musk has severely limited access to the public, imposing a $5,000 monthly charge for relevant subscriptions, although access remains open for PhD-level and post-doc-level researchers (X-API, N/A). Other alternative social media like Instagram, Facebook and Snapchat are not necessarily viable for such analysis, as they are used for more short-form personal media sharing, rather than opinions and discourse. Of course, privacy concerns and similar API limitations contribute to the challenge.

As a result, given these limitations, the viable options for proxying online social amplification for an undergraduate dissertation almost entirely comprise of public news and articles databases. Given these restrictions, I form the following hypothesis:

Hypothesis: A change in online media tone regarding economic events will result in a

change in consumer inflation expectations.

Given the limitations, the objective of this report is to simply indicate whether media tone is relevant for any policy aiming to address CIE. In the next section, I explain the data and methodology I use to address this question.

0.3 Data and Model

0.3.1 Fundação Getulio Vargas Consumer Confidence Index (FGV CCI)

The FGV CCI is this essay's dependent variable and the main proxy for CIE. It is a survey conducted by the Fundação Getulio Vargas higher education institute and think tank, sent out on a monthly frequency, to 2000 households, since 2002 across seven Brazilian state capitals: Belo Horizonte, Brasilia, Porto Alegre, Recife, Salvador, Rio de Janeiro, and São Paulo. This particular index has a few merits. One, FGV is an independent, reputable research institution, thus negating any possible biases from central bank surveys. The FGV CCI follows international standards and has been revised to ensure compliance with international standards. Two, its objective is to capture consumer sentiment and spending intentions. The survey includes 30 questions, such as whether respondents intend to buy high-value goods within the upcoming six months, providing key insights into expectations regarding economic outcomes. Finally, the use of CCI surveys as a proxy for CIE follows common academic practices, and has been tested and verified as a proxy (see Carroll, 2003; Ang et al, 2007; Souleles, 2004; Bram & Ludvigson, 1998).

0.3.2 Global Database for Events, Language, & Tone (GDELT)

On the other hand, the GDELT is used as the independent variable. It is the largest open-access database, it monitors media and news across the globe in 100 languages and spans from January 1st of 1979 until the present day with an aggregate of a quarter billion observations. From this database, I conduct original data collection, extracting 400,000 observations on Portuguese media articles, with Brazilian web domains, that mention the Brazilian economy, and their tone, across 8 years (2015-2023). The observations, captured at a 15-minute frequency average at about 4,000 monthly observations, which I collapse to monthly averages

to fit the frequency of the CCI (GDELT, N/A).

As previously mentioned, a more ideal, well-rounded social amplification proxy would have been a more dynamic dataset which would capture variables such as comments, likes, reposts and so on. However, while the GDELT captures a narrower section of the online amplification sphere, it does so effectively. Research conducted by Global Governance and the European Union on the use of the GDELT in academic settings has concluded its significant potential, even hailing its sentiment analysis performance (Saz-Caranza, 2020, P.22). Finally, the database has been cited more than 4,400 times across Google Scholar, further solidifying its reputable track.

0.3.3 Purchasing Power Parity (PPP)

To control for price signals that affect CIE and isolate the role of online social amplification, I include PPP as a control variable. The IMF PPP index, using specified baskets of goods, the PPP provides valuable insights on how real purchasing power changes for Brazilian consumers (IMF, 2018). As mentioned in the literature review, alongside social amplification, price changes serve as reference points for CIE. Thus, the inclusion of PPP helps isolate social amplification signals from price signals, reducing omitted variable bias.

0.3.4 Varieties of Democracy Multiplicative Polyarchy Index (VDEM $-$ $\mathbf{v2x}_m pi$)

Similarly to PPP, I include the VDEM democracy index to control for any political unrest that may have amplified sentiments of economic insecurity. From 2015 to 2023, Brazil experienced big political changes and many corruption scandals: its four presidents DilmaRousseff, MichelTemer, JairBolsonaro, and LuladaSilva, all faced corruption charges . However, ex-President Dilma's allegations were rejected. I use the VDEM variable Multiplicative Polyarchy Index, which captures accountability between citizens and national leaders, civil rights and freedom to control for consumer exposure to political turmoil. The data is provided at a yearly frequency, which presents some inefficiencies, however, reliable monthly frequency surveys were limited.

0.3.5 Time Frame

The selection of the 2015-2023 period was motivated by two reasons. First, I aimed to include the most recent data, given the rising phone usage rates and online access. For example, having used data from the early 2000s would have likely shown weakened results due to lower online rates. Additionally, I had collected the data in 2024, which had restricted me to data up until 2023. Second, in those eight years, two major inflationary spikes were experienced in Brazil, 10% in 2016 and 12% in 2022 (IMF, 2024). Therefore, this period provided the highest online rates and a sufficient amount of inflationary variance.

0.4 Model

In the literature review, I had shared the channels through which CIE influence economic outcomes. First, pass-through, the extent to which insumers alter their consumption and savings given a change in inflation expectations. Second, inflation inertia, the extent of which values t-1 influence current expectations. Moreover, I explained the challenges arising from inflation inertia and its irresponsible nature. Therefore, an appropriate model for answering this dissertation's research question would test whether the GDELT sample affects the CCI, its magnitude, and for how long. From these two data points, we can acknowledge whether or not online media tone– a component of online social amplification– is relevant to CIE formation. Subsequently, the model must capture elements of pass-through and contain a time-series component for capturing inertia. It follows that the VARX presents the best fit for this endeavour, given dynamic time-series capability that can capture both pass-through and inertia, formally:

$$\mathbf{y}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{y}_{t-i} + \sum_{j=0}^{q} \mathbf{B}_j \mathbf{x}_{t-j} + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}). \tag{2}$$

Where Yt Rk is a vector of endogenous variables: Fundação Getulio Vargas's Consumer Confidence Index as the consumer inflation expectations and the Global Database for Events, Language, and Tone (Brazilian economic subsaple) monthly average tone as the change in online social amplification sentiment. Alternatively, Xt Rm is a vector for the exogenous influences of variables International Monetary Fund's Purchasing Power Parity for price variation, and the Varieties of Democracy Multiplicative Polyarchy Index, for political

instabilities. Finally, t Rk represents a vector of errors. The crucial condition from this model is that all values Xt are defined exogenously, and thus Yt does not Granger-cause Xt:

$$\mathbb{E}\Big[\varepsilon_t \;\Big|\; \{Y_{t-i}\}_{i=1}^{\infty}, \{X_{t-j}\}_{j=1}^{\infty}\Big] \;=\; 0, \qquad (\,\varepsilon_t \in \mathbb{R}^k\,).$$

In other words, exogenous variables PPP and VDEM should not predict any of the endogenous variables CCI or GDELT. I test this condition using the Granger-causality test, shown in Table 1 below. I find that none of the exogenous variables show any statistically significant P-values, with all values larger than 0.05, therefore satisfying the no Granger-causality condition. Of the exogenous variables, 'PPP' and 'CCI' show the highest significance; however, still statistically significant and in line with my theoretical assumptions. Moreover, the 'GDELT_ Tone' and 'CCI' show strong statistical significance, suggesting promising results. I provide a visualisation of these results in Table 2 using a series of impulse response functions.

Table 1: Granger causality Wald tests

Equation	Excluded	χ^2	df	Prob > χ^2
GDELT_Tone	VDEM	1.180	2	0.554
	CCI	1.658	2	0.436
	PPP	0.272	2	0.873
	ALL	4.048	6	0.670
VDEM	GDELT_Tone	2.482	2	0.289
	CCI	3.208	2	0.201
	PPP	2.153	2	0.341
	ALL	8.163	6	0.226
CCI	GDELT_Tone	30.561	2	0.000
	VDEM	0.668	2	0.716
	PPP	7.584	2	0.023
	ALL	37.765	6	0.000
PPP	GDELT_Tone	1.863	2	0.394
	VDEM	0.023	2	0.989
	CCI	0.060	2	0.970
	ALL	2.069	6	0.913

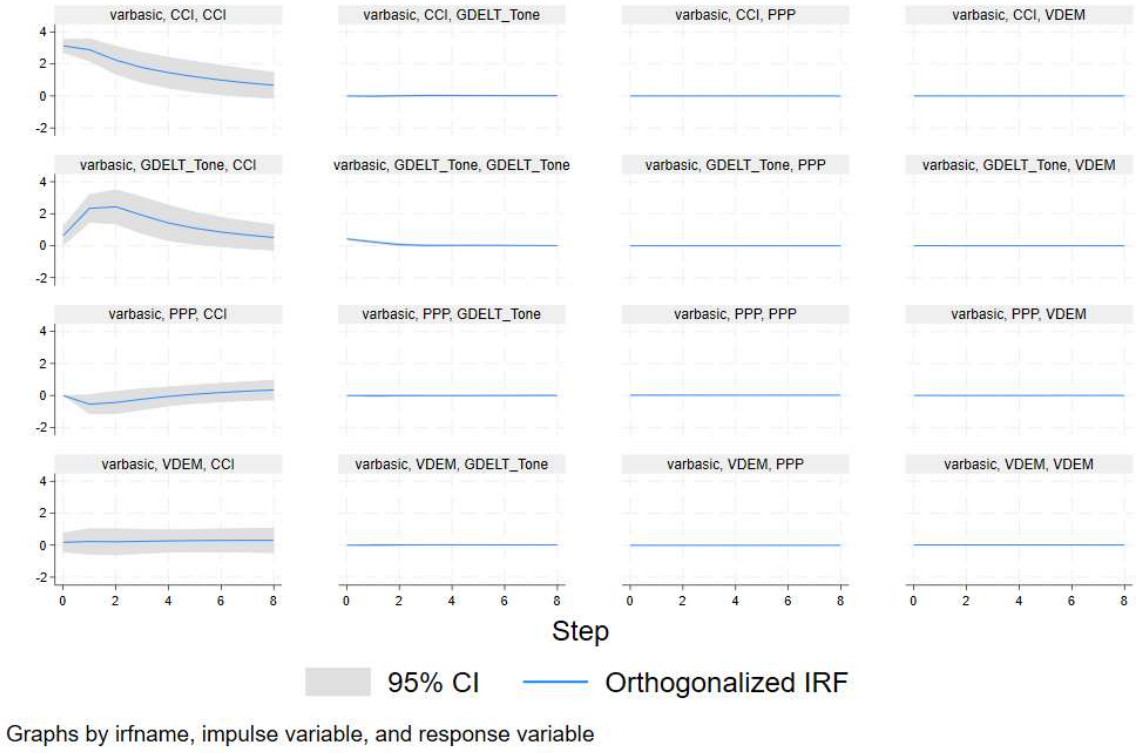

Figure 1: Impuls Response Function 1

0.4.1 Stationarity Condition

The next necessary condition the VARX model must satisfy is the stationarity of the variables (Otext, N/A; Statalist, 2020). VAR models rely on observing how different variables develop around a stable long-run mean. If the variable values are unstationary, drifting upwards or downwards, the model faces two issues. First, two non-stationary variables exhibiting upward, or any, trend may show significant fit and lag coefficients. However, the results may very likely be driven by randomness and no economic link, and thus, be misleading. Second, impulse response functions, a core feature of VAR models, rely on the assumption that shocks eventually fade. This assumption requires the stationarity of variables, and is particularly necessary for this research given its interest in inflation inertia.

Using a Philips Peron test I assess every variable in the model: PPP, CCI, GDELT_Tone, and VDEM. My null hypothesis, that variables are non-stationary and follow some trend. Using the pperron command, I find that GDELT_Tone receives a p-value ($p<0.05$), thus I reject the null hypothesis, concluding the stationarity of GDELT_Tone. Similarly, CCI satisfies the stationarity condition. However, PPP and VDEM fail to reject the null hypothesis, suggesting non-stationarity. To address this issue, I detrend PPP and VDEM, creating variables d_VDEM and d_PPP. While this removes long-term trends, it is not an issue for these variables, given they are controls.

0.4.2 Lag Lengths

Finally, to identify the most appropriate amount of lags, I use the Akaike Information Criterion (AIC), Final Prediction Error (FPE), Hannan-Quinn Information Criterion (HQIC), and Schwarz (Bayesian) Information Criterion (SBIC) tests. All of which indicate one lag length marked by the asterisk in Table 3.

Table 2: Lag–order selection criteriaSample: 2015m7–2023m12 ($N = 102$)

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	91.196					−1.710	−1.668	−1.607
1	188.829	195.27*	16	0.000	4.3×10^{-7} *	−3.310	−3.102	−2.796*
2	200.386	23.114	16	0.111	0.000	−3.223	−2.848	−2.297
3	207.902	15.030	16	0.522	0.000	−3.057	−2.515	−1.719
4	217.598	19.394	16	0.249	0.000	−2.933	−2.225	−1.183

* Optimal lag according to each criterion

0.5 Results

Finally, the main results of this paper are summarised by Table 4, the main VARX model, and Table 5, an impulse response function mapping out the effect of CIE on itself and the effect of media on CIE. In Table 4, the main VAR model, the area of interest is how the CCI– Consumer Confidence Index is influenced by GDELT_Tone. The model shows a coefficient of a fairly high 3.45 with a statistically significant p-value less than 0.001. Other statistically significant relationships include the effect of CCI on itself, which shows a coefficient of 0.79, suggesting consumers draw on past experiences of inflation quite strongly. Hence, inflation inertia is high. Additionally, media tone also carries some form of inertia with a coefficient of 0.5 in the first row. Overall, throughout the model, the exogenous control variables d_PPP and d_VDEM are statistically insignificant. However, the model itself shows positive diagnostics with a high R-squared for CCI, suggesting that the GDELT and the controls have captured about 80.13% of the variations of CCI.

Table 5, an impulse response function, which visualises how CCI responds to every change in both media tone and CCI itself. The model on the left on the effect of CCI on CCI shows how sticky inflation is for Brazilian consumers, with expectations experiencing an instantaneous 3 percentage points change at the lower 95% confidence bound up until roughly 4 percentage points. These effects then linger on for at least 6 months on the lower bound. On the right-hand side, the effect of media seems to begin with 0 effect at the 95% confidence interval, suggesting consumers don't immediately react, but rather possibly compile information over time. By the second month, expectations peak at just over three points, with a lower bound at 1.5 and an upper bound of 3.5. Eventually, the shock fades out by the eighth month at the lower bound.

These two models provide positive results with regard to the dissertation hypothesis, and indicate that: yes, changes in online media tone in Brazil result in a 3.45 point effect on consumer inflation expectations for atleast eight months. However, before engaging with the relevance of these findings to inflation and the policy sphere, I consider the model's limitations.

Table 3: VARX model summary statistics (Sample: 2015m3–2023m12)

Statistic	Value
Number of observations	106
Log likelihood	−341.517
FPE	2.603305
$\det(\Sigma_{\text{ml}})$	2.15537
AIC	6.632396
HQIC	6.734236
SBIC	6.883664

Table 4: Equation diagnostics

Equation	Parms	RMSE	R^2	χ^2	p-value
GDELT_Tone	5	0.446498	0.2673	38.66616	0.0000
CCI	5	3.50939	0.8013	427.5338	0.0000

Table 5: VARX coefficients (lag 1)

Eqn.	Regressor	Coef.	Std. Err.	z	p	95% CI
5*GDELT_Tone	$\texttt{GDELT\_Tone}_{t-1}$	0.50487	0.08879	5.69	0.000	(0.33084, 0.67895)
	$\texttt{CCI}_{t-1}$	0.00106	0.00588	0.18	0.857	(−0.01046, 0.01258)
	d_PPP	−0.87703	2.37892	−0.37	0.712	(−5.53962, 3.78556)
	d_VDEM	−1.03347	2.32722	−0.44	0.657	(−5.59472, 3.52779)
	Const	−0.53829	0.51794	−1.04	0.299	(−1.55345, 0.47659)
5*CCI	$\texttt{GDELT\_Tone}_{t-1}$	3.45257	0.69788	4.95	0.000	(2.08475, 4.82039)
	$\texttt{CCI}_{t-1}$	0.79373	0.04698	17.18	0.000	(0.70318, 0.88428)
	d_PPP	−5.06184	18.6978	−0.27	0.787	(−41.7089, 31.5852)
	d_VDEM	14.1831	18.2915	0.78	0.438	(−21.6676, 50.0338)
	Const	20.1869	4.07095	4.96	0.000	(12.2080, 28.1659)

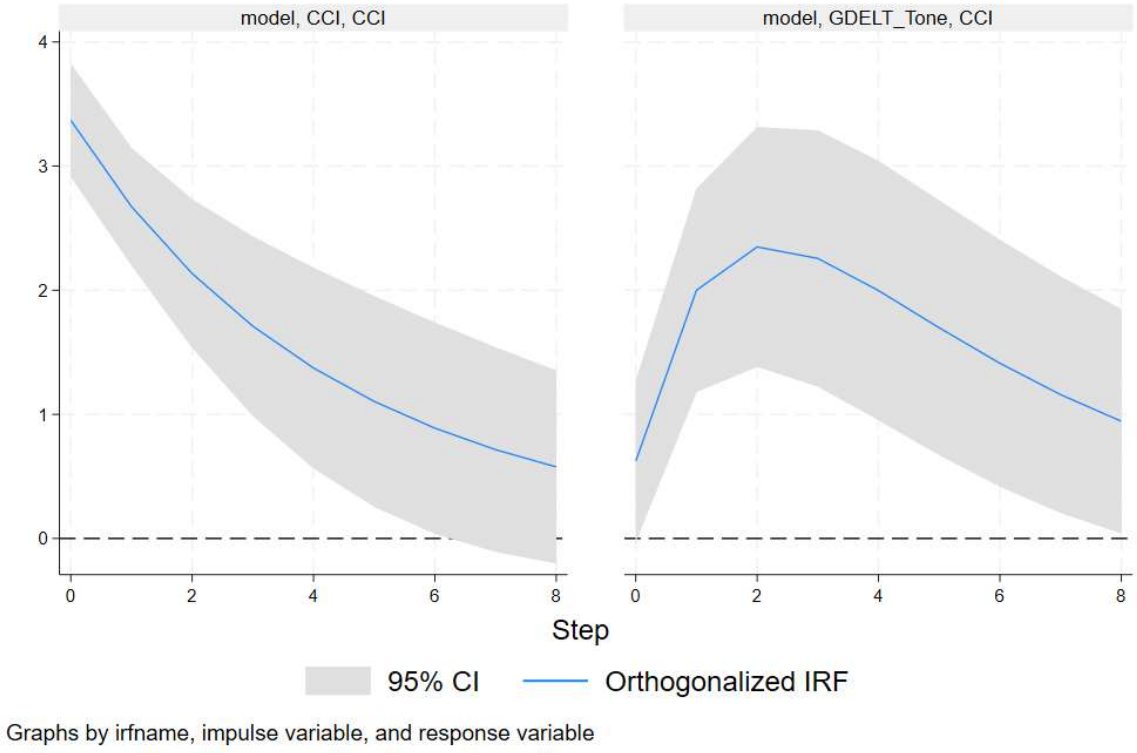

Figure 2: Impulse Response Function 2 (main)

0.6 Limitations

The first limitation for this VARX model is its assumption that CIE are linear. Throughout the eight-year sample, weightings of inputs for each component of CIE are likely to develop and shift in a non-linear manner. For example, the effect of good news versus bad news: consumers are less likely to react to good news with any particular action than they are likely to react to bad news. Yet, the model treats it like an equally weighted relationship.

The second limitation is the assumption that purchasing power and political stability are exogenous to the model, particularly over the course of eight years. Although the Granger causality test had supported the choice to include the exogenous variables, the possible effects of factors such as eroding political stability are certainly relevant. Moreover, Brazil has in fact faced significant political volatility throughout the sample period, with an impeachment and multiple presidential fraud cases. It is certainly likely that these developments have affected Brazilian consumers.

It follows that the third limitation is the frequency of the political stability of the VDEM political stability proxy. At a yearly frequency, the variable likely under-represents the important variations within the Brazilian political sphere, such as the four elections that had occurred, mass protests, and general political instability. Given the volatile unrest and the quickly shifting political dynamics and party hegemonies, the effect of these events has likely been underscored. This is possibly also an explanatory factor for the insignificance of d_VDEM as a control. Similarly, other omitted data include central bank communications and social media as other inputs into the model.

The compilation of 400,000 observations into monthly averages has resulted in the masking of the data attributes. First, it ignores the frequency of exposure to certain topics. As mentioned in the literature review, the frequency with which consumers are exposed to information regarding inflation is a key component in CIE formation. Second, it ignores the popularity, or outreach of certain news outlets over others and the disparities in their influence.

Finally, this single case study suggests the non-generalisability of these results beyond the scope of Brazil. However, I oppose the relevance of this limitation or criticism for two reasons. One, CIE mechanisms are relatively uniform across contexts (see Ranyard et al, 2008; Banerjee, 1992; Frenkel, 1976). The magnitude and weighting of each mechanism vary, however, the existence of a given mechanism holds. For example, Ranyard et al offer the Socio-Economic environment model for CIE, whether a component is relevant for a specific economic setting, regardless of the component's existence (2008). Therefore, the illustration of the online social amplification sphere as a relevant component for Brazilian consumers is

relatively generalisable, however, its magnitude for other economies may vary. Two, magnitude is arguably also generalisable, subject to central bank trust, inflation environment, and other economic factors. In a similar indicative manner, the IMF conducts generalisations dependent on the economy type (Albrizio & Bluedron, 2023). This dissertation's magnitude results are not directly transitive to other economies, however do serve as an indicative value.

0.7 Takeaway

While the limitations of this model are certainly many, the merit of this paper holds. Although not perfectly, this model, in accordance with the hypothesis, has adequately indicated that for some positive value, media tone does impact consumer inflation expectations. This is sufficient for the purpose of this essay– to indicate whether or not media tone, a component of online social amplification, is relevant for new policies aiming to address inflation through CIE. From this indication, this dissertation also sheds light on the validity of the threat of online social amplification as a contributor to inflation. Moreover, taking a broader step backwards, these findings suggest that the internet is a source of signals utilised by consumers for IE formation. I emphasise this point– that if online media articles affect inflation expectations, it is then plausible to assume that other aspects of the internet similarly play a role. Subsequently, under-regulated, high-traffic platforms like Twitter, TikTok, Facebook, Reddit, Instagram, and WhatsApp begin to suggest similar threats to inflation stability. Additionally, my findings and the aforementioned assumptions are particularly in line with the surrounding literature. Both supporting the more general notion: in a volatile inflation environment, with a non-credible central bank, consumers will begin to search for alternative sets of signals in an attempt to overcome inflation volatility. Subsequently, in the final section, Policy Discussion, I offer speculative insight into possible angles from which a policymaker or economist may need or choose to address these emerging challenges stemming from CIE and the online sphere.

0.8 Policy Discussion

Before addressing possible policy considerations, I break down this issue into a signalling and screening game. On the signalling side exist central banks, inflation rates, professional forecasts, social amplification, price changes, and, as shown online media articles. These signals are inputs for CIE. On the other hand, consumers screen for these signals and respond accordingly. Their subsequent actions manifest in the form of pass-through effects or

inflation inertia. To reiterate, I approach policy options by addressing, signalling issues– how can policymakers mitigate, or possibly eliminate online social signals that affect CIE. And, screening issues– how policymakers can mitigate how consumers perceive negative inflation signals. Finally, I suggest a third alternative (or additive) of using these findings to motivate forecasting tools, and how such a forecasting tool may be deemed useful. .

0.8.1 Signaling

Online social amplification signals can pose a series of challenges, which potentially require the attention of policymakers. If consumers screen for IE signals from the online sphere, then they are subject to misinformation and bias amplification– two prevalent threats. These threats are extensive, well-documented and certainly far beyond the scope of this essay. However, as a reference, the World Economic Forum's 2024 Global Risk Report has ranked 'Misinformation and Disinformation' as the number one most severe threat to global security in the next two years, and the 7th (and first non-environmental) most severe issue in the next ten years (WEF, 2024, p.8). Moreover, many governments are struggling to 'keep up' with this issue and the growing digital sphere. In an article by Carugati et al, they highlight how governments have in fact lost their monopoly over online digital spheres, and how the threat of these failures ultimately leads to governance failures and security issues (2023). Therefore, the issue of online social amplification signals is twofold, I attempt to explain this through the following logic:

Assumption1: Consumers rely on online media articles to form IE (and likely other online sources).
Assumption 2: Changes in CIE feed through consumption and saving changes, and ultimately, overall economic outcomes.
Assumption 3: Online media ecosystems are subject to large amounts of disinformation and misinformation, which can distort economic signals.
Assumption 4: Governments are failing to monopolise and govern digital spheres, hence failing to address disinformation and misinformation.

Therefore, the government's inability to govern and address digital misinformation and disinformation can unanchor and create volatile CIE, hence, destabilising macroeconomic outcomes. It follows that an appropriate government policy from an online signalling perspective must increase its digital capacity and limit online economic information falsities and biases.

0.8.2 Screening

On the other hand, screening presents a relatively narrower challenge: how consumers perceive these online social amplification signals. US Federal Reserve Board member Jeremy Rudd jokingly offered that the best solution to consumer screening challenges, is to remove all CIE signals (2021). The less people hear about inflation, the better. On the other hand, a more serious report from the European Central Bank indicates that with increased efforts, central banks can ground CIE in the face of exogenous volatile information signals. The report stresses that efforts must be made to address different types of consumers, and capturing their attention (ECB, 2024). A similar report from the EU Center for Economic Policy Research found that medium types influence consumer attention grasp, with audiovisual mediums dominating traditional static text and images (EUCPR, 2024). Subsequently, to obtain consumer attention, central banks must adapt and update their strategies with the rapidly changing 'economy of attention'. As Herbert A. Simon had put it fifty years ago in 1971; "a wealth of information creates a poverty of attention". Central banks must learn overcome this burden in order to inform and ground citizen expectations.

Additionally, such strategic progressions are not foreign in the governmental sphere. Many global leaders have garnered significant social media followings in a bid for attention and influence. The US President Donald J. Trump currently holds 104 million X followers, India's Prime Minister Narendra Modi has 66 million Instagram followers, similarly Brazil's ex-President won the 2018 elections with minimal TV time, relying heavily on social media presence (Belli, 2018). Likewise, central banks must target consumers with strategies that effectively hold attention. As of now, only two central banks hold more than 1 million social media followers: Federal Bank of India (2.3 million X followers) and the US Federal Reserve Board (1.2 million X followers). Moreover, whether through social media, or not, central banks should consider new strategies for engaging in the attention economy. Particularly, in the midst of other of highly volatile, and unverified economic information.

0.8.3 Forecasting

Finally, the findings in this essay offer particularly promising forecasting relevance. As shown in the main findings, the impact of media on CIE only reaches its peak after two months, hence, offering a lag period for central banks to respond. By utilising this continuous stream of information offered by the digital sphere regarding economic sentiment, central banks can indicate when to act more swiftly with regards to CIE grounding.

0.9 Conclusion

To conclude, this dissertation has explained the threat of inflation and the role of CIE in this threat. Subsequently, I put forth the hypothesis: A change in online media tone regarding economic events will result in a change in consumer inflation expectations. To test this hypothesis, I conducted original data collection on online media tone regarding the economy. I presented the model I used– a VARX with two endogenous variables, GDELT (media tone) and CCI (inflation expectations), and exogenous variables, PPP (changes in prices) and VDEM (political stability). I then shared the results that a marginal change in tone results in a 3.5 point change in inflation expectations after two months, which eventually lingers for atleast eight months. Additionally, I show that Brazilian inflation inertia potentially holds for atleast six months, thus adding to the effect of media tone. Using these findings, I verify my hypothesis, acknowledging my model's critical limitations. However, I argue, that the merit of the results survives. Towards the end of the essay, I provide speculative policy accounts of these results with respects to signaling, screening, and forecasting. Overall, I share the concern that for central banks and governments to engage with this issue, they must become more engaged themselves within the online sphere.

Appendix

Table 6: Description of variables used in the empirical analysis

Symbol	**Role**	**Definition / Construction**	**Source**	**Freq. / Xform.**
`GDELT_Tone`	Endogenous	Monthly average of online media article *tone* in Portuguese across Brazilian on economic topics. Collected from GDELT (400 k observations collapsed to month means).	GDELT GKG 2.0 Event Database	Monthly (level)
`CCI`	Endogenous	Consumer Confidence Index by Fundação Getulio Vargas (FGV): used as proxy for consumer inflation expectations.	FGV – Fundação Getulio Vargas	Monthly (index level)
`PPP`	Exogenous	Purchasing Power Parity price-level index for Brazil.	IMF – International Monetary Fund	Anual (level)
`d_PPP`	Exogenous	First difference of `PPP` to remove non-stationary trend.	Derived	Anual ()
`VDEM`	Exogenous	Multiplicative Polyarchy Index measuring electoral and civil–liberty dimensions of democracy (VDEM – v2x_mpi)	V-Dem v13 dataset	Annual (level)
`d_VDEM`	Exogenous	Detrended (first-differenced) `VDEM` Monthly ()		

Bibliography

[1] Albrizio, Silvia and John Bluedorn. "How Managing Inflation Expectations Can Help Economies Achieve a Softer Landing." *IMF Blog*, 4 Oct. 2023. https://www.imf.org/en/Blogs/Articles/2023/10/04/how-managing-inflation-expectations-can-help-economies-achieve-a-softer-landing

[2] Ang, Andrew *et al.* "Do macro variables, asset markets, or surveys forecast inflation better?" *Journal of Monetary Economics* **54**(4) (May 2007), 1163–1212. DOI:10.1016/j.jmoneco.2006.04.006

[3] Banerjee, A. V. "A simple model of herd behavior." *The Quarterly Journal of Economics* **107**(3) (Aug. 1992), 797–817. DOI:10.2307/2118364

[4] Barnett, Alina *et al.* "Time-varying inflation expectations and economic fluctuations in the United Kingdom: A structural VAR analysis." *SSRN Electronic Journal* (2010). DOI:10.2139/ssrn.1619793

[5] Bates, John M. and André Gabor. "Price perception in creeping inflation: Report on an enquiry." *Journal of Economic Psychology* **7**(3) (Sept. 1986), 291–314. DOI:10.1016/0167-4870(86)90022-x

[6] Beckmann, Joscha *et al.* "What drives updates of inflation expectations? A Bayesian VAR analysis for the G-7 countries." *The World Economy* **45**(9) (Mar. 2022), 2748–2765. DOI:10.1111/twec.13241

[7] Belli, Luca. "Opinion: WhatsApp Skewed Brazilian Election, Showing Social Media's Danger to Democracy." *PBS NewsHour*, 5 Dec. 2018. https://www.pbs.org/newshour/science/whatsapp-skewed-brazilian-election-showing-social-medias-danger-to-democracy

[8] International Monetary Fund. "Brazil and the IMF." IMF, 21 Aug. 2024. https://www.imf.org/en/Countries/BRA

[9] Bresser-Pereira, Luiz Carlos. "The Theory of Inertial Inflation: A Brief History." *Brazilian Journal of Political Economy* (5 May 2023). DOI:10.1590/0101-31572023-3433

[10] Bryan, Michael F. *et al.* "The inflation expectations of firms: What do they look like, are they accurate, and do they matter?" *SSRN Electronic Journal* (2015). DOI:10.2139/ssrn.2580491

[11] Carroll, C. D. "Macroeconomic expectations of households and professional forecasters." *The Quarterly Journal of Economics* **118**(1) (Feb. 2003), 269–298. DOI:10.1162/00335530360535207

[12] Carugati, Federica *et al.* "The Sensitive Politics of Information for Digital States." *NOEMA*, 14 Mar. 2023. https://www.noemamag.com/the-sensitive-politics-of-information-for-digital-states/

[13] Coibion, Olivier, Dimitris Georgarakos, *et al. How Does Consumption Respond to News about Inflation? Field Evidence from a Randomized Control Trial.* Working Paper, July 2019. DOI:10.3386/w26106

[14] Coibion, Olivier, Yuriy Gorodnichenko, *et al.* "Inflation expectations as a policy tool?" *Journal of International Economics* **124** (May 2020), Article 103297. DOI:10.1016/j.jinteco.2020.103297

[15] Fundação Getulio Vargas (FGV). "Consumer Survey." IBRE, 2020. https://portalibre.fgv.br/en/estudos-e-pesquisas/indices-de-precos/sondagem-do-consumidor

[16] DataReportal. "Digital Around the World – Global Digital Insights." Accessed 8 May 2025. https://datareportal.com/global-digital-overview

[17] Duarte, Fabio. "Alarming Average Screen Time Statistics (2025)." *Exploding Topics*, 24 Apr. 2025. https://explodingtopics.com/blog/screen-time-stats

[18] Duca, Ioana *et al.* "Inflation expectations, consumption and the lower bound: Micro evidence from a large Euro Area survey." *SSRN Electronic Journal* (2018). DOI:10.2139/ssrn.3285079

[19] D'Acunto, Francesco *et al. The Effect of Unconventional Fiscal Policy on Consumption Expenditure.* Working Paper, Aug. 2016. DOI:10.3386/w22563

[20] Eden, Benjamin. "The Welfare Cost of Inflation and the Regulations of Money Substitutes." World Bank, 2016. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/722561468196744155/the-welfare-cost-of-inflation-and-the-regulations-of-money-substitutes

[21] Fan, Chengze Simon and Phoebe Wong. "Does consumer sentiment forecast household spending?" *Economics Letters* **58**(1) (Jan. 1998), 77–84. DOI:10.1016/S0165-1765(97)00247-4

[22] Hyndman, Rob J. and George Athanasopoulos. *Forecasting: Principles and Practice* (2nd ed.), Chap. 11.2 "Vector Autoregressions." Accessed 9 May 2025. https://otexts.com/fpp2/VAR.html

[23] Frenkel, Jacob A. "Inflation and the formation of expectations." *Journal of Monetary Economics* **1**(4) (Oct. 1976), 403–421. DOI:10.1016/0304-3932(76)90011-8

[24] The GDELT Project. "About the GDELT Project." Accessed 9 May 2025. https://www.gdeltproject.org/about.html

[25] Ha, Jongrim *et al.* "What explains global inflation." *IMF Economic Review* (11 July 2024). DOI:10.1057/s41308-024-00255-w

[26] European Central Bank. "Household Inflation Expectations: An Overview of Recent Evidence." ECB Discussion Paper, 2024. https://www.ecb.europa.eu/pub/pdf/scpdps/ecb.dp24~9b349a69b7.en.pdf

[27] Adrian, Tobias. "The Role of Inflation Expectations in Monetary Policy." Remarks at the IBF/Deutsche Bundesbank Symposium, IMF, 15 May 2023. https://www.imf.org/en/News/Articles/2023/05/15/sp-role-inflation-expectations-monetary-policy-tobias-adrian

[28] Ichiue, Hibiki and Shusaku Nishiguchi. "Inflation expectations and consumer spending at the zero lower bound." Bank of Japan Working Paper #13E11, 2013. https://www.boj.or.jp/en/research/wps_rev/wps_2013/data/wp13e11.pdf

[29] CETIC.br. *ICT Households Survey 2023 – Executive Summary.* 2024. https://www.cetic.br/media/docs/publicacoes/2/20240826110205/executive_summary_ict_households_2023.pdf

[30] International Monetary Fund. "IMF Inflation (Consumer Prices, Percent Change)." Accessed 2024. https://www.imf.org/external/datamapper/PCPIPCH@WEO/BRA

[31] Istrefi, Klodiana and Anamaria Piloiu. "Economic policy uncertainty and inflation expectations." SSRN Working Paper, 17 Oct. 2014. DOI:10.2139/ssrn.2510829

[32] Kasperson, Roger E. *et al.* "The social amplification of risk: A conceptual framework." *Risk Analysis* **8**(2) (June 1988), 177–187. DOI:10.1111/j.1539-6924.1988.tb01168.x

[33] Redline Digital. "Key Statistics on Fake News & Misinformation in Media in 2024." 2024. Accessed 8 May 2025. https://redline.digital/fake-news-statistics/

[34] Lamla, Michael J. and Sarah M. Lein. "The role of media for consumers' inflation-expectation formation." *SSRN Electronic Journal* (2008). DOI:10.2139/ssrn.1150774

[35] Murtfeldt, Ryan *et al.* "RIP Twitter API: A eulogy to its vast research contributions." arXiv preprint arXiv:2404.07340, 10 Apr. 2024. https://arxiv.org/abs/2404.07340

[36] Twitter Developer Platform. "Non-Commercial Use of the X API." Accessed 9 May 2025. https://developer.x.com/en/developer-terms/commercial-terms

[37] Parker, Miles. "How global is 'global inflation'?" *Journal of Macroeconomics* **58** (Dec. 2018), 174–197. DOI:10.1016/j.jmacro.2018.09.003

[38] Pidgeon, Nick *et al.* "Introduction." In *The Social Amplification of Risk*, 10 July 2003,1–10. DOI:10.1017/CBO9780511550461.001

[39] International Monetary Fund. "Purchasing Power Parity: Weights Matter." 15 June 2018. https://www.imf.org/en/Publications/fandd/issues/Series/Back-to-Basics/Purchasing-Power-Parity-PPP

[40] Ranyard, Rob *et al.* "Perceptions and expectations of price changes and inflation: A review and conceptual framework." *Journal of Economic Psychology* **29**(4) (Aug. 2008), 378–400. DOI:10.1016/j.joep.2008.07.002

[41] Rudd, Jeremy B. "Why do we think that inflation expectations matter for inflation? (and should we?)." *Finance and Economics Discussion Series* 2021-062 (Sept.2021), 1–27. DOI:10.17016/feds.2021.062

[42] Saz-Carranza, Ángel *et al. The Empirical Use of GDELT Big Data in Academic Research.* 2020. https://www.globe-project.eu/the-empirical-use-of-gdelt-big-data-in-academic-research_13809.pdf

[43] Centre for Economic Policy Research. "Seeing and HearingIsBelieving: The Role of Audiovisual Communication in Shaping Inflation Expectations." 2024. https://cepr.org/voxeu/columns/seeing-and-hearing-believing-role-audiovisual-communication-shaping-inflation

[44] Simon, Herbert A. "Designing organizations for an information-rich world." In M. Greenberger (ed.), *Computers, Communication, and the Public Interest*. Johns Hopkins Press, 1971, 37–52. https://veryinteractive.net/pdfs/simon_designing-organizations-for-an-information-rich-world.pdf

[45] Soroka, Stuart N. "Good news and bad news: Asymmetric responses to economic information." *The Journal of Politics* **68**(2) (May 2006), 372–385. DOI:10.1111/j.1468-2508.2006.00413.x

[46] Souleles, Nicholas S. "Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan consumer sentiment surveys." *Journal of Money, Credit, and Banking* **36**(1) (2004), 39–72. DOI:10.1353/mcb.2004.0007

[47] Vellekoop, Nathanael and Mirko Wiederholt. "Inflation expectations and choices of households." *SSRN Electronic Journal* (2019). DOI:10.2139/ssrn.3383452

[48] World Economic Forum. *The Global Risks Report 2024*. 2024. https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2024.pdf

[49] International Monetary Fund. "World Economic Outlook Database – Groups and Aggregates." 8 Apr. 2023. https://www.imf.org/en/Publications/WEO/weo-database/2023/April/groups-and-aggregates

[50] Jiang, Zachary and contributors. "VAR Models." Statalist forum thread, 2 Nov. 2020. https://www.statalist.org/forums/forum/general-stata-discussion/general/1579930-questions-about-components-stationarity-in-var-model