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Theoretical-empirical Article

Expectations, Economic Uncertainty, and Sentiment

Expectativas, Incerteza Econômica e Sentimento

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ABSTRACT

Objective: this article aims to help unravel if and how economic uncertainty interacts with the informational structure of sentiment. **Methods:** the empirical strategy is based on a non-linear and non-parametric causality test to investigate the interaction between variables as distributions. This article builds primarily on the literature on expectation formation. **Results:** it was found that uncertainty based on the media (ex-ante) precedes sentiment, at most, until the second moment of its distribution. In addition, sentiment helps predict the informational structure of fundamental uncertainty (ex-post) and higher order moments of ex-ante uncertainty. **Conclusion:** sentiment can be considered a channel for uncertainty through the tone of expectations and erroneous expectations. Ex-ante uncertainty measures can also help calibrate the rational cost-benefit calculation of attention by acting as a leading indicator of the increasing value of information.

Keywords: expectations; economic uncertainty; sentiment; causality tests.

RESUMO

Objetivo: o presente artigo pretende ajudar a desvendar se e como a incerteza econômica interage com a estrutura informacional do sentimento. **Métodos:** a estratégia empírica baseia-se em teste de causalidade não linear e não paramétrico para investigar a interação entre as variáveis enquanto distribuições. Este artigo constrói principalmente a partir da literatura sobre formação de expectativas. **Resultados:** foi encontrado que a incerteza com base na mídia *(ex-ante)* antecede o sentimento, no máximo, até o segundo momento de sua distribuição. Além disso, o sentimento ajuda a prever a estrutura informacional da incerteza dos fundamentos (*ex-post*) e momentos de ordem superior da incerteza *ex-ante*. **Conclusão:** sentimento pode ser considerado um canal para incerteza através do tom das expectativas e de expectativas errôneas. Medidas de incerteza *ex-ante* podem ainda ajudar a calibrar o cálculo racional custo-benefício da atenção ao atuar como indicador antecedente do maior valor da informação.

Palavras-chave: expectativas; incerteza econômica; sentimento; testes de causalidade não linear.

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INTRODUCTION

Sentiment is defined as the optimistic or pessimistic tone of expectations, capable of impacting production, consumption, investment, inflation, and stock prices, in part without basis on economic fundamentals. In this case, when the sentiment is not justified by the facts, the expectations turn out to be erroneous. Therefore, sentiment has an expectational (ex-ante) and composed nature, formed by a rational and an irrational component (Barsky & Sims, 2012; Lahiri & Zhao, 2016; Nowzohour & Stracca, 2020; Verma & Soydemir, 2009).

It is also known that the expectations formation process occurs largely as a reaction to *news* (information) (Friedman, 1979; Pearce & Roley, 1985), but *noise* also affects expectations (Chahrour & Jurado, 2018; Nowzohour & Stracca, 2020). The greater difficulty in distinguishing information from noise is a possible mechanism by which economic uncertainty produces erroneous expectations and inefficient decisions (Banerjee & Green, 2015; Black, 1986; Daniel, Hirshleifer, & Teoh, 2002; Daniel, Hirshleifer, & Subrahmanyam, 2001; Kahneman & Tversky, 1973; 1982; Kumar, 2009; Nowzohour & Stracca, 2020).

In addition, seminal literature related to heuristics and biases approach considers situations of uncertainty as a factor that triggers irrationality in the expectations formation process (Black, 1986; Kahneman & Tversky, 1973; 1979; 1982; Kahneman, 2003; Keynes, 1936; Tversky & Kahneman, 1974). For Kahneman and Tversky (1973; 1979) and Black (1986), uncertainty is closely associated with noise and irrationality in expectations. Nevertheless, empirical research that explicitly aims to elucidate the relation between uncertainty and sentiment is rare, so that this relation remains theoretically and empirically obscure (Baker, Bloom, & Davis, 2016).

In turn, economic uncertainty is defined as situations in which, for a given set of courses of action, the probabilities that certain outcomes will occur is unknown. Under uncertainty, drawing future scenarios is possible, but it is not possible to estimate the probabilities of realization of these scenarios (Knight, 1921). In fact, it is not known exactly which measure is closest to the true latent generating process of economic uncertainty; however, as in the case of sentiment, some proxies have been developed allowing for new empirical tests (Baker et al., 2016; Jurado, Ludvigson, & Ng, 2015), as in the present article.

It can be seen that the research agenda on sentiment remains active, committed to developing an understanding of its informational structure, its determinants, its effects, and the construction of new measures for sentiment (Alti & Tetlock, 2014; Kaplanski & Levy, 2017; Shen, Yu, & Zhao, 2017; Sibley, Wang, Xing, & Zhang, 2016).

This article aims to help clarify 'if' and 'how' sentiment can be considered another channel through which uncertainty can impact markets. Through an empirical approach, it explicitly addresses the relation between uncertainty and sentiment from measures of uncertainty and sentiment for Brazil. The proposed objective also implies the identification of a possible mechanism for the 'correction' of erroneous expectations.

The present investigation also suggests the possible extraction of proxies for the irrational component of sentiment from measures of uncertainty with informational content related to expectations. In this context, it is plausible to speak of construction of measures for noise, in the sense of Black (1986) — a measure that does not yet exist in the empirical literature. The most suitable measures of sentiment and uncertainty for empirical studies in the Brazilian economy were also identified.

Based on the results, it is possible to point out a new look at the practical usefulness of ex-ante economic uncertainty indicators, as they can signal the moment of obtaining gains with the allocation of greater attention to information. This is because greater attention can nudge the expectations formation process toward rationality, in order to promote efficiency in decisions (Gigerenzer & Gaissmaier, 2011; Löfgren & Nordblom, 2020; Sims, 2003).). In this way, uncertainty measures can help calibrate the rational cost-benefit calculation about obtaining information. The findings obtained here contribute to the literature on nudging and choice architecture.

In short, this article innovates by (a) explicitly dealing with the dynamic relationships between the informational structures of uncertainty and sentiment, as well as the economic interpretation of these relations; (b) assigning a new function to ex-ante economic uncertainty measures; and (c) pointing out a possible path for the construction of 'noise' measures, in the Black's (1986) sense, so far non-existent in the literature and capable of providing new tests, especially for sentiment and nudging models.

To investigate the existence of dynamic causal relations between uncertainty and sentiment, the nonlinear and nonparametric causality tests developed by Diks and Panchenko (2005; 2006) were used and, as well as the three-step testing strategy suggested by Bekiros and Diks (2008a; 2008b), in a complementary way. These methodological procedures allowed evidence of Granger causality relations involving moments of higher order of the distributions, which can reveals the informational structure of the variables (Bekiros & Diks, 2008a; 2008b; Shefrin, 2008).

In addition to this introduction, the following section surveys the relevant literature; the third section sets out the empirical procedures; the forth section reports and discusses the results of the empirical analysis; finally, the final considerations highlight the findings and their implications.

LITERATURE REVISION

Relationship between uncertainty and sentiment

The process of expectations formation and decision-making by economic agents (consumers, entrepreneurs, governments, experts, and risk investors) depends on the information set available and information reactions. However, for expectations and decisions to be considered rational (and efficient), the decision-maker needs to have a complete understanding of the 'true' economic model, constantly follow the latest information, and efficiently process this information (Friedman, 1979; Pearce & Roley, 1985).

Agents commonly obtain a sight of the economy from media news, so the media strongly influences the formation and updating of expectations (Alti & Tetlock, 2014; Carroll, 2003; Doms & Morin, 2004; Friedman, 1979; Pearce & Roley, 1985; Rambaccussing & Kwiatkowski, 2020; Tetlock, 2007).

Intuitively, agents' expectations can be represented according to probability theory and probability density functions. Haddow, Hare, Hooley and Shakir (2013) suggest that the result perceived as most likely is represented by the first moment of distribution, associated with the level of confidence of economic agents. The dispersion of results perceived by agents as more likely (second moment) is related to uncertainty.

It should be noted that shocks to uncertainty would rarely be dissociated from shocks at other moments in the distribution, especially during crises (Haddow, Hare, Hooley, & Shakir, 2013; Ilut & Schneider, 2014). More precisely, uncertainty is defined as the inability to predict probabilities associated with certain events (Keynes, 1936; Knight, 1921).

It is also common to distinguish uncertainty from risk — where risk is the knowledge of the probability distribution of certain events, although what will actually happen is not known (Knight, 1921). According to Rossi, Sekhposyany and Souprez (2018), after the 2007/2008 global financial crisis, uncertainty remained at high levels and became more important than risk, as measured by realized volatility.

Under uncertainty, it is theoretically predicted that economic agents follow an expected utility function of the maxmin type (maximize among the worst expected results), that is, they form expectations taking into account the worst possible scenario. Agents tend to become more uncertainty-averse and pessimistic as uncertainty increases and, as a result, tend to overreact to bad news and under-react to good news (Bird & Yeung, 2012; Gilboa & Schmeidler, 1989).

Uncertainty aversion also implies that the pessimist believes that bad news is more persistent than good news. This is because agents can observe the true state of the economy, but they do not know the true transition probabilities between a growth regime and a contraction regime in economic activity. Thus, the persistence of the state of expansion would be perceived in a pessimistic way, which results in distorted expectations toward low economic growth rates (Caskey, 2009; Cecchetti, Lam, & Mark, 2000).

For the capital market, Dicks and Fulghieri (2021) theoretically predict that uncertainty aversion will (endogenously) cause fluctuations in expectations between pessimism and optimism. This occurs in face of innovation, which is a factor in the expectations formation, which, by nature, is characterized by limited knowledge about the probability distributions for successful investments.

These authors use a rational approach to sentiment, which depends on the uncertainty of economic fundamentals: the more diffuse the waves of innovation, allowing for the diversification of investments in stocks of innovative companies, the greater the optimism. According to this theory, optimistic moments (hot markets) would be associated with high valuations and greater activity in IPOs, mergers, and acquisitions involving technology companies.

The theoretical and empirical literature on business cycles documents various channels through which uncertainty counter-cyclically impacts markets (Bloom, 2014). Due to the effect of real options, investments and contracts, which are difficult to reverse, are postponed by companies, which start to wait for the arrival of information to resolve uncertainties (Bernanke, 1983; Bloom, 2009; Pindyck, 1991). The risk premium effect is responsible for reducing investment and consumption after increasing the risk premium required for new financing (Bansal & Yaron, 2004; Liu & Miao, 2015). The precautionary saving effect generates postponement of consumption due to fears on future income downturns (Bansal & Yaron, 2004;

Bloom, 2014). These channels of uncertainty are related to perceptions and expectations that cause protection decisions, consistent with rationality.

However, as far as is known, there is no research indicating sentiment as a possible channel for uncertainty. However, in a seminal work, Black (1986) associates uncertainty with noise and *animal spirits* — a term used by Keynes (1936) to refer to psychological aspects that affect decisions —, which are pointed out as responsible for instability and bubble formation in the markets. This author also pointed out the heuristics and biases approach as an explanation for the relation between uncertainty and the irrational component of sentiment.

However, uncertainty affects other aspects of expectations, not necessarily pessimistic. Birru and Young (2020) argue that, in the absence of probabilities to be attributed to potential outcomes, decision-makers will have fewer grounds on which to base their decisions. They point out that the literature related to the behavioral approach to decision-making details systematic deviations from rationality under conditions of uncertainty.

As a result, when a specific task, such as making forecasts, is vague and has ambiguous assumptions, agents tend to follow patterns and stereotypes rather than expend greater efforts in obtaining and processing information (Griffin & Tversky, 1992; Kahneman & Tversky, 1973; Kahneman, 2003). Experimental evidence suggests that overconfident investors may exhibit behavior inconsistent with uncertainty aversion and more subjective and error-prone judgments (Birru & Young, 2020; Heath & Tversky, 1991; Olsen & Troughton, 2000).

It has been observed that overconfidence grows with the degree of difficulty of predictions and judgments and when timely information is not available to confirm or deny previously obtained information or decisions (Griffin & Tversky, 1992; Lichtenstein, Fischhoff, & Phillips, 1982). Furthermore, experts aware of their expertise in a certain field may become overconfident, underestimating the variance of their predictions (calibration bias) (Barber & Odean, 2001).

Overconfidence and calibration biases can also appear combined with cognitive conservatism about new and accurate signals. Bloomfield, Libby and Nelson (2000) found that agents can overreact to unconfirmed information, while assuming a conservative attitude in the face of precise and clear signals. They can also place a lot of importance on extreme information that is in the spotlight, such as news that is prominent in the media, regardless of its real value. Such attitudes can be reflected in the stock market as overreacting to unreliable information and under-reacting to precise and clear signals.

Based on models with noise traders, Daniel, Hirshleifer and Subrahmanyam (2001) and Kumar (2009) found that the greatest uncertainty related to a group of stocks predicts more intense effects of investor irrationality. Baker and Wurgler (2006; 2007) and Stambaugh, Yu and Yuan (2012) demonstrate that investor irrationality affects more stocks with greater uncertainty in their valuation, such as stocks with less time listed in stock exchange, small cap companies and with greater volatility in their returns.

For the economy as a whole, Barsky and Sims (2012) decomposed the innovations in consumer sentiment into a component related to animal spirits and another related to the information received by the consumer and found that the future levels of economic activity mainly reflect the information component. However, Chahrour and Jurado (2018) demonstrated that the business cycle literature has underestimated the importance of fluctuations in the business cycle caused by expectations not explained by real changes in economic fundamentals.

As seen, the optimistic or pessimistic tone of expectations is defined as sentiment, in part not based on fundamentals. Nevertheless, sentiment is best defined as a distribution and its informational structure. Shefrin (2008) suggests that other moments should also be taken into account: a second moment (standard deviation) of the distribution, related to risk perception; a third moment (asymmetry), which captures concerns about downturns in economic activity, even in moments of optimism; and a fourth moment (kurtosis), associated with the attribution of high probabilities for the occurrence of extreme events, such as, for example, the stock market crash.

In addition to the effects of biases and heuristics, Rossi et al. (2018) point out two other mechanisms of transmission of sentiment to the markets: self-fulfilling prophecies and *news* (information or signal) and *noise*. Sentiment can not only describe future perspectives on developments in the economy but also determine these developments, as they influence investment decisions in the present. Therefore, the sentiment can generate self-fulfilling prophecies, with permanent effects if justified by the facts, or temporary, otherwise (Barsky & Sims, 2012; Chahrour & Jurado, 2018; Lahiri & Zhao, 2016; Lemmon & Portniaguina, 2006; Nowzohour & Stracca, 2020; Verma & Soydemir, 2009).

Blanchard, L'Huillier and Lorenzoni (2013) and Banerjee and Green (2015) found that decision-makers solve a signal extraction problem, that is, they do not easily distinguish between news and noise. Agents continually receive information to be used in the formation of expectations, which can turn out to be factual information or just noise. Based on this information, these agents choose expenditures and, given the nominal rigidity of prices, expenditures affect production and prices in the short run. The authors found that if the information is effective ex-post, the economy gradually adjusts to the new level of activity. However, revealing only noise, activity and prices return to their initial state.

The irrational component of sentiment therefore consists of erroneous expectations or errors, involving all the aforementioned statistical moments of its distribution (Shefrin, 2008), which can be defined as erroneous expectations, not completely justified by economic fundamentals and with reversible effects in the short term (Baker & Wurgler, 2006; Black, 1986; Nowzohour & Stracca, 2020).

Even the media, an important element of the informational structure of the economy, can induce erroneous expectations (Chahrour & Jurado, 2018). Doms and Morin (2004) discovered that consumer sentiment responds to the tone and volume of economic news reported in the media. Furthermore, according to the model proposed by Gennaioli, Shleifer and Vishner (2015), the representativeness bias induces agents to overestimate the probability of results that are relatively more likely in light of data recently observed in the media.

Consistent with rational behavior, Gorodnichenko (2008) showed that information acquisition can grow endogenously soon after the occur-rence of an aggregate shock. In these situations, given the increase in uncertainty related to current state of the economy, agents would perceive it as advantageous to employ more resources to obtain information, reducing uncertainty.

Faced with uncertainty, agents with limited attention (and limits to rationality) face situations where the optimization of choices demands considerable effort. To reduce or avoid this effort, individuals come to rely on intuition or habit, which can lead to mistakes (Gigerenzer & Gaissmaier, 2011; Löfgren & Nordblom, 2020). In these situations, Löfgren and Nordblom (2020) suggest that non-mandatory interventions in the structure of choices, in order to 'push' expectations toward rationality (also known as nudges), would be effective.

A better understanding of how agents form their expectations requires taking into account that decision-makers choose their degree of attention from a cost-benefit analysis: more attention and analytical effort will be allocated if the cost of obtaining more information is more than offset by the expected benefit (Gigerenzer & Gaissmaier, 2011; Gorodnichenko, 2008; Löfgren & Nordblom, 2020; Sims, 2003).

Another important issue to be considered when analyzing the relation between uncertainty and sentiment is nonlinearities. These can arise from structural breaks (Hiemstra & Jones, 1994); variation in the pattern of reaction to the flow of information (Bird & Yeung, 2012; Ross, 1989); bubbles with self-fulfilling expectations (Blanchard & Watson, 1982; Chahrour & Jurado, 2018); nonlinear monetary policies (Flood & Isard, 1989); and the action of noise traders (Black, 1986; Francis, Mougoué, & Panchenko, 2010; Long, Shleifer, Summers, & Waldmann, 1990). For uncertainty in Brazil, high volatility can generate nonlinearities in the series (Ferreira, Oliveira, Lima, & Barros, 2017), and persistence of shocks of different signals can have a different impact on the uncertainty itself (Souza, Zabot, & Caetano, 2019).

Measures for uncertainty and sentiment

In periods of high economic uncertainty, the dispersion of expectations increases (Haddow et al., 2013; Scotti, 2016), it becomes more difficult to predict economic scenarios (Jurado et al., 2015), and uncertainty becomes a recurrent theme in the media (Baker et al., 2016).

Jurado, Ludvigson and Ng (2015) suggested a measure of fundamental uncertainty adhering to the theoretical notion of Knightian uncertainty in order to measure the unpredictability of economic scenarios. The measure was built from a set of economic indicators that represent economic fundamentals. Formally, the uncertainty of an economic variable was defined according to the identity expressed in Equation 1:

$$Inc_{jt}^{y}(h) \equiv \sqrt{E\left[\left(y_{jt+h} - E\left[y_{jt+h}|\mathbb{I}_t\right]\right)^2|\mathbb{I}_t\right]} \tag{1}$$

with $j = 1, \ldots, N_y$. The expectation $E\left[y_{jt+h}|\mathbb{I}_t\right]$ denotes the forecasts h periods ahead of several economic indicators, conditional on the information available. y_{jt+h} are the realizations of economic indicators. $Inc_{jt}^{y}(h)$ corresponds to the stochastic volatility of the forecast errors (unpredictable component of each series y). From this definition, the authors obtained a measure of economic uncertainty from the aggregation of individual uncertainties Inc_{jt}^{y}.

Baker, Bloom and Davis (2016) developed an uncertainty measure based on the frequency of terms related to economic or economic policy uncertainty in a group of newspapers, as Equation 2:

$$\mathrm{P_{k,t}} = \frac{\mathrm{I_{k,t}}}{\mathrm{T_{k,t}}} \tag{2}$$

where $P_{k,t}$ is the proportion of news about uncertainty in month t; $T_{k,t}$ is the total amount of news published by media k in month t; and $I_{k,t}$ is the amount of news with terms related to economic uncertainty.

Kahneman and Tversky (1982) observe that the increase in the uncertainty perceived by agents implies an increase in the probability of expression in natural language of terms related to the perceived uncertainty. Therefore, the measure of uncertainty based on the media would also be able to reflect the degree of uncertainty subjectively perceived by economic agents.

Rossi et al. (2018), when investigating the dynamics of inflation expectations, found that ex-ante uncertainty measures are appropriate to capture aspects of the expectations formation process. In turn, ex-post measures are appropriate to guide economic policy, so that the most effective policy to reduce inflation uncertainty is those that affect ex-post uncertainty. The authors identified that the measure of uncertainty proposed by Baker et al. (2016) is determined more by ex-ante uncertainty, while the measure proposed by Jurado et al. (2015) is affected by ex-post uncertainty.

The literature documents that during recessions consumer sentiment indicators are meticulously observed, as any significant change or lack thereof is considered a very valuable signal informing about a near inflection point or prolongation of depressed states in economic activity (Vuchelen, 2004).

Sentiment proxies, composed of a component explained by economic fundamentals and another orthogonal to fundamentals, reflect behavioral aspects of economic agents. Consumer confidence indicators (CCI), built on survey data from a sample of respondents, are frequently used in empirical research and help predict both business cycle variables and stock returns (Baker & Wurgler, 2006; Barsky & Sims, 2012; Bird & Yeung, 2012; Chahrour & Jurado, 2018; Lahiri & Zhao, 2016; Lemmon & Portniaguina, 2006; Nowzohour & Stracca, 2020; Qiu & Welch, 2006; Stambaugh, Yu, & Yuan, 2012; Verma & Soydemir, 2009). For Brazil, Graminho (2015), after orthogonalizing CCI to macroeconomic variables, confirmed the existence of a component of sentiment related to animal spirits.

Nevertheless, the literature documents other methodologies for constructing sentiment proxies. For a measure of investor sentiment directly obtained in the stock market, Baker and Wurgler (2006) used the first main component of a set of proxies hitherto consolidated in the finance literature, mainly the number of IPOs. It is worth noting that in Brazil there are considerable restrictions to obtain a version of the Baker and Wurgler's (2006) sentiment index. The absence of data similar to the USA data used in the original measure and the short historical series have been the main restrictions (Yoshinaga & Castro, 2012).

Rambaccussing e Kwiatkowski (2020) mapped qualitative media news, such as expert opinions, on a quantitative basis sentiment proxy, capable of successfully predicting economic activity and stock returns. They claim that a potential explanation for the success of the forecasts obtained is because the news in the media brings informational content related to self-fulfilling prophecies, especially in the case of speculative bubbles, bank runs, and financial crises.

The literature on the construction of measures for investor sentiment highlights that to unravel the nature of sentiment it is necessary to identify its determinants. Sibley, Wang, Xing and Zhang (2016) uncover that 65% of the explanatory power of Baker and Wurgler's (2006; 2007) investor sentiment index is determined by macroeconomic variables. Lahiri and Zhao (2016) analyzed the informational content of consumer sentiment and identified as important determinants the perception of recent economic news, the perception of consumers about the performance of economic policy, and consumer expectations about the level of employment and inflation.

In this context, few empirical studies explore the hypothesis that economic uncertainty operates as a determinant of sentiment. However, some research touches on this problem. Bird and Yeung (2012) found that high sentiment prevailing at the beginning of the period can mitigate the effect of economic uncertainty; in this case, agents may overreact to good news even with high uncertainty, which challenges the uncertainty aversion hypothesis.

Birru and Young (2020) additionally showed that the predictive power of sentiment in relation to stock returns increases in periods of high uncertainty (associated with the upper quintiles of the historical distribution of returns). They argue that high uncertainty is associated with more subjective and error-prone valuation of assets.

As stated, the literature suggests that variations in uncertainty affect other moments of a probability density function that represents expectations, but does not explicitly clarify 'how' this occurs (Haddow et al., 2013; Shefrin, 2008). This article contributes to mitigate this gap from empirical research involving proxies for economic uncertainty and sentiment. Then, the methodology used in this investigation will be explained.

METHODOLOGICAL PROCEDURES

To achieve the proposed objective, parametric linear causality tests, developed by Granger (1969), and nonparametric nonlinear causality tests proposed by Diks and Panchenko (2006), henceforth DP test, were implemented. This test has the advantage of its robustness to structural breaks and its comparability with Granger's definition of causality (Bekiros, Gupta, & Kyei, 2016; Diks & Panchenko, 2006).

Data and variables

Monthly frequency data were used for the period 02/2002–12/2019, a period in which most of the series studied are available. Uncertainty measures were selected according to their nature, one ex-post and another ex-ante, as well as their acceptance in the literature.

In the first case, it was replicated the fundamental uncertainty measure suggested by Jurado et al. (2015), hereinafter abbreviated as INC. A set of economic indicators representing economic fundamentals, $\mathbb{I}_t$, was used, encompassing product, prices, consumption, civil construction, currency and credit, exchange rate, and capital market (not reported; available upon request).

In the second case, the following were used: (a) uncertainty in the media-based economic policy (EPU) for Brazil, with a methodology developed by Baker et al. (2016) (available at www.policyuncertainty.com retrieved on December 15, 2019); and (b) media component of the IIE-BR economic uncertainty indicator, computed by the Brazilian Institute of Economics (IBRE/FGV), here denoted by IEM.

The main difference in the construction of EPU and IEM is the number of media included in the database. The variable IEM was constructed from the newspapers *Valor Econômico, Folha de São Paulo, O Globo, Estado de São Paulo* and *Correio Brasiliense*, as well as the digital media channels of these newspapers. EPU was built only from the database of the *Folha de São Paulo* newspaper (Ferreira et al., 2017).

It is important to note that EPU is sensitive to biases, emphases, and perspectives of the only media used in its construction, which generates more intense fluctuations in EPU in relation to IEM. In the case of IEM, the greater number of media used promotes neutrality and smoother oscillations through the contraposition of opposites.

The measure for sentiment used was the consumer confidence index (CCI), constructed from questionnaire data. An important advantage is that its informational structure directly captures aspects of the expectations formation process. CCI^{FGV} was used, published by the Getulio Vargas Foundation (FGV), as well as CCI^{FEC}, published by the Federation of Commerce of São Paulo (Fecomércio). There are some differences that are worth noting: (a) CCI^{FGV} started to be computed in 2005, while CCI^{FEC} started in 2000; and (b) CCI^{FEC} started in 2000; and (b) CCIFEC involves respondents from only one capital, São Paulo, and CCI^{FGV} is more comprehensive, involving several capitals, obtaining greater macroeconomic representation.

Due to the availability of relatively short historical series, the analyses could not be segmented, which constitutes a limitation for the present investigation.

Linear and parametric causality test

For the null hypothesis that the variable X_t does not cause Y_t, in the sense of Granger (1969), the traditional Granger causality test equation can be written as

$$Y_t = \gamma + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \beta_j X_{t-j} + \varepsilon_t \tag{3}$$

where γ is a constant, p and q are the length of lags sufficient to make the disturbance term, ε, a white noise, and t is the time. The null hypothesis implies that $\beta_1 = \beta_2 = \cdots = \beta_q = 0$.

It should be noted that causality in Granger's sense should not be interpreted as causality in its strict sense, but as the temporal advance of a variable X in relation to variable Y, where X helps predict Y.

Nonlinear and nonparametric causality tests

Diks and Panchenko (2006) developed a nonparametric method used to test the nonlinear causality relationship between two stationary time series, consistent with Granger's definition of causality, which can be described as follows.

Assume that $\{X_t, Y_t, t \geq 1\}$ are two strictly stationary time series. $\{X_t\}$ strictly causes Granger $\{Y_t\}$ if the past and current values of X contain additional information about the future values of Y, which are not contained in the present and past values of Y_t.

Also consider the lag vectors $X_t^{\ell_X} = (X_{t-\ell_X+1}, \dots, X_t)$ and $Y_t^{\ell_Y} = (Y_{t-\ell_Y+1}, \dots, Y_t)$, $(\ell_X, \ell_Y \geq 1)$. The null hypothesis that the past observations of $X_t^{\ell_X}$ do not contain useful information for Y_{t+1} can be described by Equation 4:

$$H_0 : Y_{t+1} | (X_t^{\ell_X}; Y_t^{\ell_Y}) \approx Y_{t+1} | Y_t^{\ell_Y} \tag{4}$$

where ≈ denotes equivalence in distribution. For two strictly stationary time series, Equation 4 will actually consider the distribution in the dimension vector $(\ell_X + \ell_Y + 1)$, $W_t = (X_t, Y_t, Z_t)$, where $Z_t = Y_{t+1}$. The distribution of W_t will be invariant under null. We exclude the temporal index and assume $\ell_X = \ell_Y = 1$. Then, under the null, the conditional distribution of Z, given by $(X, Y) = (x, y)$ is equivalent to the conditional distribution of Z, given by $Y = y$. In Equation 4, the joint probability distribution density $f_{X,Y,Z}(x,y,z)$ and its marginal must satisfy the following equation:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)} \tag{5}$$

Equation 5 implies that X and Z are conditionally independent with respect to $Y = y$, for each fixed value of y. Therefore, the null hypothesis formulated by Diks and Panchenko (2006) implies the following equation:

$$q = E\left[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)\right] = 0 \tag{6}$$

It follows that $\hat{f}_W(W_i)$ denotes a local density estimator of a random vector W in W_i and in the dimension d_W, defined by:

$$\hat{f}_W(W_i) = \frac{(2\varepsilon_n)^{-d_W}}{n-1}\sum_{j\neq i} I_{ij}^W \tag{7}$$

where $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon_n)$, $I(\cdot)$ is the indicator function and ε_n the bandwidth, which depends on the sample size n. Given this estimator, the test statistic for estimating q will be:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)}\sum_i \left(\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)\right) \tag{8}$$

Then, it is possible to verify that for $d_X = d_Y = d_Z = 1$ and letting the bandwidth depend on the sample size, so that $\varepsilon_n = Cn^{-\beta}$, for $C > 0$ and $\frac{1}{4} < \beta < \frac{1}{3}$, the T_n test statistic will satisfy the condition

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{d} N(0,1) \tag{9}$$

where $\xrightarrow{d}$ denotes convergence in distribution and S_n is an estimator of the asymptotic variance σ^2 of T_n. Hence, the statistic T_{n,ε_n} will have a standard normal distribution as its limiting distribution.

Three-step DP testing and the informational structure

As a complement to the DP test, Bekiros and Diks (2008a; 2008b) proposed a three-step filtering procedure. This procedure allows making inferences about causality involving other moments of the variables distributions, which allows analyzing the sentiment informational structure, as suggested by Shefrin (2008). If a statistically significant nonlinear Granger causality relation persists until the third step, it will be possible to infer that the relation involves higher order moments. If the prior relation is statistically significant at all steps, then the Granger causal relation will include the entire information structure.

In the procedure first step, both linear and nonlinear causal relations are analyzed based on the raw (unfiltered) data of the variables. The second step consists of filtering the data, removing its linear structure through bivariate autoregressive vector models, VAR(p), with p lags, as specified in Equations 10.1 and 10.2. This model takes into account lagged values of the variable itself and current and lagged values of the other variable. Then, the DB test is repeated for the residuals, u_{xt} and u_{yt}, which represents series orthogonal to linear relationships between the variables x and y.

$$X_t = \beta_{x0} + \beta_{x1}X_{t-1} + \cdots + \beta_{xk}X_{t-k} + \alpha_{x1}Y_{t-1} + \cdots + \alpha_{xk}Y_{t-k} + u_{xt} \tag{10.1}$$

$$Y_t = \beta_{y0} + \beta_{y1}Y_{t-1} + \cdots + \beta_{yk}Y_{t-k} + \alpha_{y1}X_{t-1} + \cdots + \alpha_{yk}X_{t-k} + u_{yt} \tag{10.2}$$

In the third step, the data is filtered through a generalized autoregressive conditional heteroscedasticity model, GARCH(p, q), with p lags for the square of the error and q lags for conditional variance. This model captures the effects of variance in the time dependence of the series (while the VAR model focuses only on the mean). Then, the residuals were used as inputs to again implement the DP test.

Specifically, an extension of the GARCH(1,1) model, sensitive to asymmetries in the temporal dependence of the shocks, was used. Asymmetry occurs when shocks of different signals (+/-) and/or magnitudes impact differently the pattern of dependence of a time series (Souza et al., 2019). Dependency patterns reflect human behavior, so asymmetries can arise, for example, because agents overreact to bad news (Bird & Yeung, 2012; Lahiri & Zhao, 2016). Thus, the Glosten, Jagannathan and Runkle's (1993), model was implemented, abbreviated as GJR-GARCH(p, q), capturing asymmetry in any direction. The GJR-GARCH model just changes the specification of the conditional variance function of the traditional GARCH model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \quad (11)$$

where σ_t^2 is the conditional variance in the next period. The asymmetry term, γ, will be positive if asymmetric responses to shocks u_{t-1} occur. $I_{t-1} = 1$ if $u_{t-1} < 0$ and $I_{t-1} = 0$ if $u_{t-1} > 0$. Finally, in this third step, the residuals obtained through the estimation of Equation 11, for each series, are again submitted to the DP test.

RESULTS ANALYSIS AND DISCUSSION

DP tests used first-difference sentiment time series, given its non-stationarity. The series for uncertainty proved to be stationary. Table 1 reports the results for the stationarity tests. The following variables were tested: uncertainty based on media, or ex-ante (EPU, IEM), fundamental uncertainty, or ex-post (INC), and sentiment (CCI^{FGV}, CCI^{FEC}).

Figure 1 shows the correlation matrix. At the top, the (absolute) values of the correlations were reported. At the bottom, bivariate scatter plots, with the line fitted. On x'the diagonal, the empirical distributions.

Table 1. Unit root tests.

	Period 09/2005–12/2017				
	EPU	IEM	CCI^{FEC}	CCI^{FGV}	INC
Only intercept: ADF	4.0303**	4.7181***	1.9316	1.6410	5.7213***
Tendency and intercept: ADF	7.6448***	5.5951***	1.8775	2.0828	5.6044***

Note. This table reports the results of level stationarity tests. The null hypothesis of the augmented Dickey-Fuller (ADF) test is the existence of a unit root (Dickey & Fuller, 1981). The optimal lag was chosen using the Schwarz information criterion (SIC). The asterisks *, **, and *** denote the rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

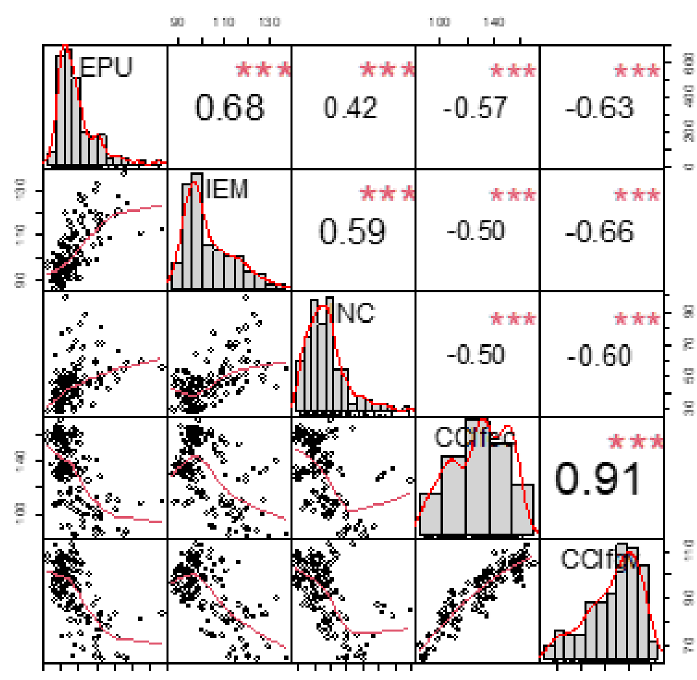

Figure 1. Correlations between variables for uncertainty and sentiment.
Period 09/2005–12/2017. ≤ 1% (***), ≤ 5% (**), ≤ 10% (*). Source: Own elaboration.

It is interesting to notice in the scatter plots changes in the sign of the relations, at certain threshold values; this is the case of cor(IEM, INC), cor(IEM, CCI^{FGV}) and cor(INC, CCI^{FGV}), indicating nonlinearities, consistent with the literature (Bird & Yeung, 2012; Chahrour & Jurado, 2018; Francis et al., 2010).

On the diagonal, it is possible to see that measures for uncertainty and sentiment have asymmetries in their distributions, with opposite patterns, where all measures for uncertainty are skewed to the right.

Uncertainty of fundamentals (ex-post) and sentiment

Initially, a visual inspection in Figure 2 allows a notion of the historical trajectory of the studied series. Vertical lines indicate points in time at which some relevant uncertainty events occurred. The proxy for fundamental uncertainty, INC, is capable of capturing the effects on the unpredictability of the economy from uncertainty events. Most of the time, sentiment (CCI^{FGV}) follows the opposite path, consistent with the uncertainty aversion hypothesis.

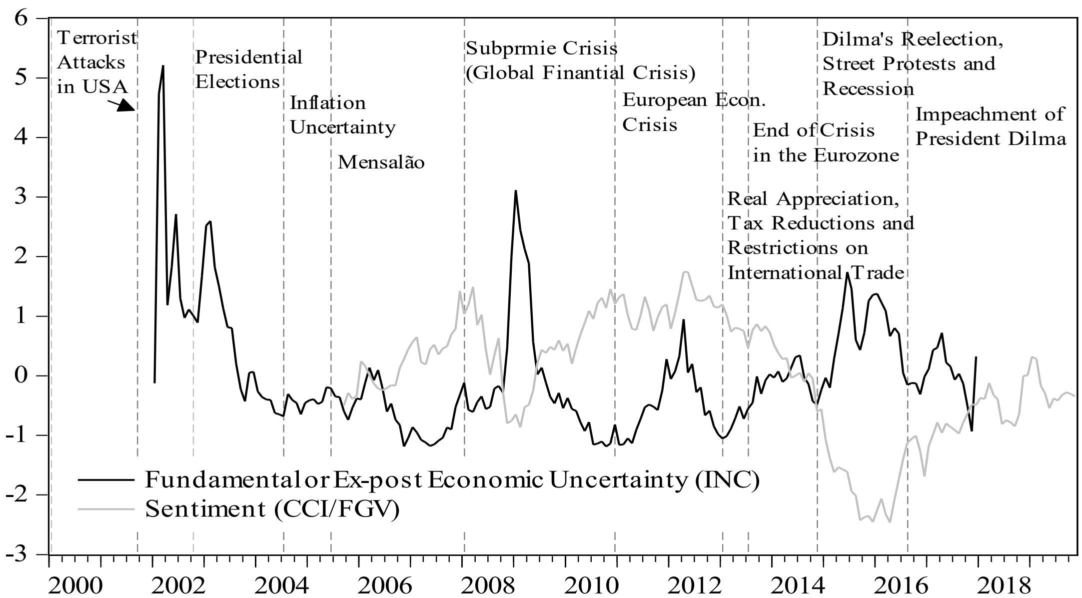

Figure 2. Uncertainty of fundamentals and sentiment in Brazil.
Standardized data. Source: Own elaboration.

The results for the causality tests are reported in Tables 2 to 4. The statistic T_{n,ϵ_n}, with the lag size of order 1 to 3, that is $\ell_x = \ell_y = 1, 2,$ or 3, and width of band ϵ_n, had the optimal size $\epsilon_n = 1{,}78$, defined as a function of sample size. As a convention, following the literature, (***) and (**) will be interpreted as strong relationships, while (*) means a significant but weak causal relationship. The significance of the relationships was reported for the number of lags in which a statistically significant causal relationship first appeared.

Table 2 shows the results of linear and nonlinear causality tests for the ex-post economic uncertainty series (INC), based on fundamentals, $\mathbb{I}_t$, and sentiment, approximated by versions of the consumer confidence index (CCI^{FGV} and CCI^{FEC}). For linear causality tests, the period of analysis was 11/2008–12/2017, considering the existence of a structural break for the series in 11/2008. For the INC→CCI^{FGV} relation (read "INC causes in the sense of Granger CCI^{FGV}") the period 10/2005–12/2017 was used for the nonlinear test, considering that the nonlinear and nonparametric tests are robust to structural breaks. For INC→CCI^{FEC}, the nonlinear test comprised the period 02/2002–12/2017.

Table 2 shows the existence of the CCI^{FGV}→INC relation. The fact that this relation persists in nonlinear causality tests for all three steps means that CCI^{FGV} has predictive power in relation to INC involving moments of higher order, that is, the entire informational structure of sentiment precedes ex-post uncertainty (Bekiros & Diks, 2008a; 2008b; Diks & Panchenko, 2006; Shefrin, 2008).

Table 2. Linear and nonlinear causality tests: INC and CCI.

Pairs		Linear causality		Nonlinear and nonparametric causality					
X:	*Y:*	Raw data		Raw data		VAR		GJR-GARCH	
		$X \nrightarrow Y$	$Y \nrightarrow X$	$X \nrightarrow Y$	$Y \nrightarrow X$	$X \nrightarrow Y$	$Y \nrightarrow X$	$X \nrightarrow Y$	$Y \nrightarrow X$
INC	$CCI^{FGV}(2)$		***		**		*		*
INC	$CCI^{FEC}(1)$	***							

Note. $X \nrightarrow Y$ (X does not cause Granger Y) is the null hypothesis. Statistical significance: ≤ 1% (***), ≤ 5% (**), ≤ 10% (*). Source: Own elaboration.

To analyze these results, consider initially (a) that INC corresponds to the unpredictable aggregate components, obtained from a large number of economic indicators, $\mathbb{I}_t$, used as predictors (Jurado et al., 2015) and (b) that part of the sentiment is determined by fundamentals (Chahrour & Jurado, 2018; Graminho, 2015; Lahiri & Zhao, 2016; Verma & Soydemir, 2009), included in $\mathbb{I}_t$. Thus, consistent with the literature, sentiment (CCI^{FGV}) has informational content not contained in the fundamentals (Cecchetti et al., 2000; Chahrour & Jurado, 2018; Nowzohour & Stracca, 2020), as well as in the lagged values of INC, capable to anticipate ex-post economic uncertainty.

The findings reported in Table 2 are still consistent with Blanchard et al. (2013) and Chahrour and Jurado (2018), who claim that both the rational component and the irrational component of expectations impact the economy in the short term.

Therefore, sentiment may help predict fundamental economic uncertainty two months ahead. In an economic interpretation, the level of optimism (average), risk perception (variance), concerns about the slowdown in economic activity (asymmetry), and attribution of high probabilities to extreme events (kurtosis), as well as erroneous expectations corresponding to each of these moments of CCI^{FGV} distribution, precede changes in INC (Bekiros & Diks, 2008a; 2008b; Shefrin, 2008). The same does not happen with CCI^{FEC}, which can be explained by the fact that CCI^{FEC} captures the perceptions and expectations of a more restricted group of respondents (São Paulo), while INC have greater informational wealth and greater economic representation.

Uncertainty based on media (ex-ante) and sentiment

Figure 3 shows the temporal trajectories of ex-ante economic uncertainty, as measured by IEM, and sentiment, as measured by CCI^{FGV}. These are the most economically significant measures, as justified below. Both series show less persistence than the fundamental uncertainty indicator seen in Figure 2, which demonstrates that they are susceptible to shorter-term forces.

The results of the linear and nonlinear causality tests between ex-ante economic uncertainty measures — IEM and EPU — and sentiment measures – CCI^{FGV} and CCI^{FEC} — for the period 11/2008–06/2019 were summarized in Table 3.

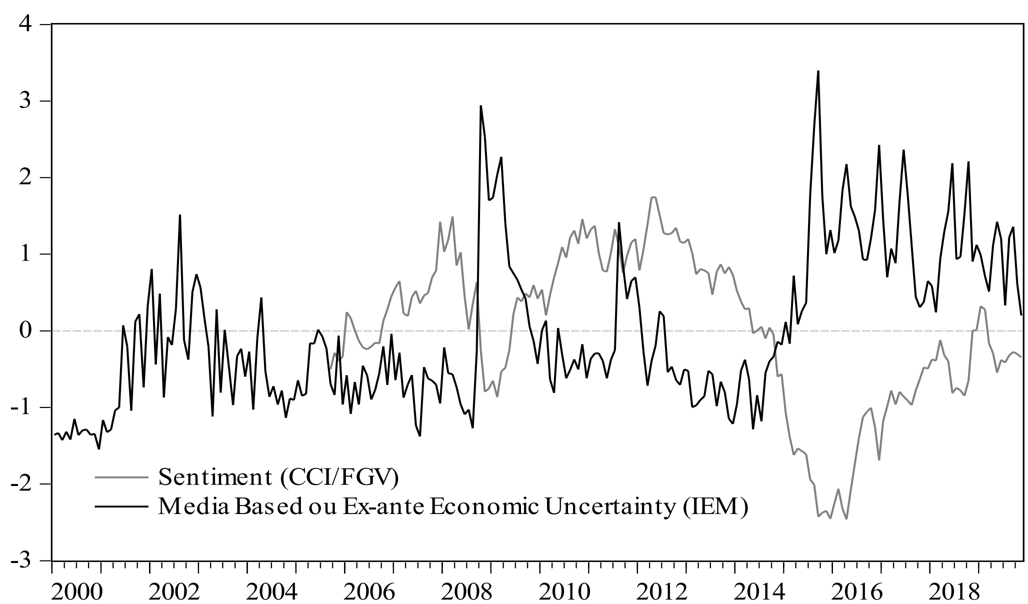

Figure 3. Uncertainty based on media and sentiment to Brazil.
Standardized data. Source: Own elaboration.

Table 3. Linear and nonlinear causality tests: EPU, IEM, and CCI.

Pairs		Linear causality		Nonlinear and nonparametric causality					
X:	*Y:*	Raw data		Raw data		VAR		GJR-GARCH	
		$X \nrightarrow Y$	$Y \nrightarrow X$	$X \nrightarrow Y$	$Y \nrightarrow X$	$X \nrightarrow Y$	$Y \nrightarrow X$	$X \nrightarrow Y$	$Y \nrightarrow X$
EPU	$CCI^{FGV}(3)$				*	*		*	
EPU	$ICC^{FEC}(2)$			*			*		*
IEM	$CCI^{FGV}(2)$	***	**	*			**		**
IEM	$CCI^{FEC}(2)$	*		**					

Note. $X \nrightarrow Y$ (*X* does not cause Granger *Y*) is the null hypothesis. Statistical significance: 1% (***), 5% (**), 10% (*). Source: Own elaboration.

The relation CCI^{FGV}→EPU occurs in a nonlinear and weak way, but after filtering the data by the bivariate VAR model, it emerged in relation to EPU→CCI^{FGV} in a strictly nonlinear and weak way. Therefore, EPU has predictive power for higher order moments of CCI^{FGV} and, following Shefrin (2008), in an economic interpretation, it is possible that EPU helps predict changes in risk perception, concerns about the reversal of the state of activity, and expectations about the occurrence of extreme events.

When CCI^{FGV} is replaced by CCI^{FEC} in the analysis, the opposite happens, the sentiment starts to precede the uncertainty involving only moments of higher order, in a strictly nonlinear and weak way. However, it is noteworthy that this same pattern of causality is repeated in the relation between IEM and CCI^{FGV}, when a strictly nonlinear and strong relationship is revealed.

It is important to note that these last two results are similar to those observed in Table 2, for INC and CCI^{FGV}. A plausible explanation for the presented pattern is the homogeneity in the representativeness of the variables. Thus, it is possible to conclude (a) that the non-homogeneity of sentiment and uncertainty measures weakens the statistical significance; and (b) that CCI^{FGV} (IEM) is informationally superior to CCI^{FEC} (EPU).

In short, when there is homogeneity in the representativeness between the variables, the relations "sentiment → ex-post uncertainty" become clearer for the entire informational structure, and "sentiment → ex-ante uncertainty" for higher order moments. Economically, changes in risk perception, concerns about the reversal of the state of activity, even in moments of optimism, and high probabilities attributed for occurrence of extreme events precede uncertainty.

The literature indicates that uncertainty can also be represented by probability density functions (Rossi, Sekhposyany, & Souprez, 2018), and it is plausible to conclude that CCI^{FGV} and CCI^{FEC} have information capable of anticipating variations in higher order moments of the measure for uncertainty perception.

You can see another recurring pattern in Table 3. The IEM→CCI^{FGV} and IEM→CCI^{FEC} relations occur linearly and nonlinearly. It should be noted (a) that the linear Granger causality relation IEM→CCI^{FGV} is significantly stronger, despite the homogeneity in representativeness between them; and (b) that the IEM→CCI^{FGV} relation does not survive the second and third steps of the data filtering procedure, showing that IEM helps predict the level of optimism and risk perception (including non-rational component). It is also accepted, according to the literature, the interpretation that the agents' uncertainty helps explain the value of the information, a direct function of the uncertainty (Sims, 2003).

In addition to the fact that IEM and CCI^{FGV} are at the same level of aggregation, take into account, according to Rossi et al. (2018), which measures of ex-ante uncertainty are more appropriate to understand aspects of the formation of expectations. Thus, IEM and CCI^{FGV} are adequate proxies for the study of the relation between uncertainty and sentiment because both have an expectation nature.

Not least, there was a linear double causality between IEM and CCI^{FGV} in the second lag, consistent with a possible overlap of information (Baker et al., 2016; Haddow et al., 2013). However, double causality disappears at longer lags (not reported).

Relation between measures of economic uncertainty

Given the difference in the construction of measures for uncertainty used here, it is convenient to deepen the analysis considering now the relationship between them. This subsection can further be considered a robustness test in two respects: distinction between their informational structures and empirical confirmation or refutation of the expectative (ex-ante) nature of media-based uncertainty measures. Initially, a visual inspection of the measures for uncertainty (homogeneous in representativeness) should be done, as shown in Figure 4.

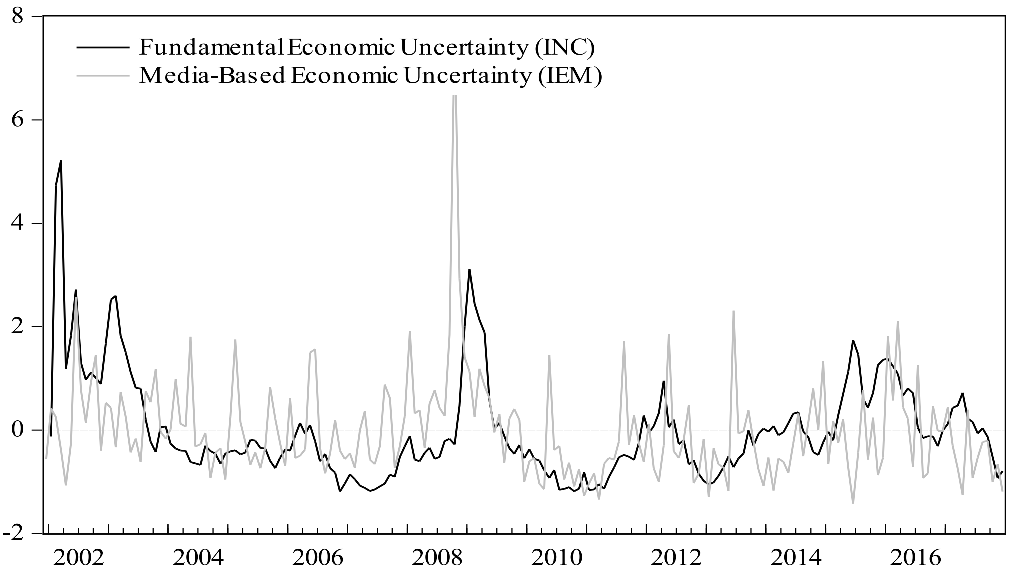

Figure 4. Uncertainty of fundamentals, ex-post, and sentiment in Brazil.
Standardized data. Source: Own elaboration.

INC is most strongly related to lagged IEM values, which corroborates the ex-ante nature of IEM. It can be seen that the ex-ante measure has a shorter-term dynamic; in this sense, IEM has low persistence (0.35) compared to INC (0.83).

As reported in Table 4, some patterns are prominent: (a) there is double causality in the relation between the EPU and IEM variables, indicating information overlap, throughout their information structure. The significantly stronger advance of IEM is also clear, which can be attributed to its greater informational richness; and (b) there is advance of media-based measures, that is, EPU and IEM, on the uncertainty of the fundamentals, INC, in all its information structure, what evidences the expectational nature of the former.

Table 4. Linear and nonlinear non-causality tests for economic uncertainty measures.

Pairs		Linear causality		Nonlinear and nonparametric causality					
X:	*Y:*	Raw data		Raw data		VAR		GJR-GARCH	
		X ↛ Y	Y ↛ X	X ↛ Y	Y ↛ X	X ↛ Y	Y ↛ X	X ↛ Y	Y ↛ X
EPU	IEM(1)		**	*	***	*	*	*	*
EPU	INC(2)	**	**	*	*	**		**	
IEM	INC(1)	**	***	*		*		*	

Note. $X \nrightarrow Y$ (X does not cause Granger Y) is the null hypothesis. Statistical significance: 1% (***), 5% (**), 10% (*). Source: Own elaboration.

The advance of ex-ante measures in relation to ex-post measures, which is expected, actually shows not only their nature of expectations, but another facet of the real effects of expectations, where ex-ante measures help resolve part of the ex-post uncertainty (Chahrour & Jurado, 2018).

The literature (Black, 1986; Kahneman & Tversky, 1982) and the results obtained here suggest that there is another practical implication: increases in ex-ante uncertainty measures indicate a greater probability of the occurrence of erroneous expectations and decisions, as well as undesired outcomes. IEM and EPU can indicate when the cost of greater sacrifice in obtaining information may be more than offset by the benefit obtained (Gorodnichenko, 2008; Löfgren & Nordblom, 2020).

Therefore, it is possible that IEM and EPU can give a 'little push' toward the formation of rational expectations because it helps inattentive agents calibrate the rational calculation of the cost-benefit relation of information gathering by signaling information value increases as uncertainty increases (Gorodnichenko, 2008; Kahneman & Tversky, 1982; Löfgren & Nordblom, 2020; Sims, 2003).

FINAL CONSIDERATIONS

The results found show that economic uncertainty, quantified from the media, is an economic determinant for sentiment. It was observed that sentiment acts as a channel for uncertainty as it impacts the formation of expectations. Hence, part of the predictive power of sentiment measures can be attributed to ex-ante uncertainty.

Notably, the parametric and nonparametric tests showed that uncertainty, measured by IEM, informationally precedes sentiment (CCI^{FGV} and CCI^{FEC}), although the significance has faded after applying the linear filter. This fact implies that this Granger causality relationship occurs within the first and, at most, second moment, that is, it involves aspects related to the degree of optimism and risk perception, not always based on fundamentals.

Considering that some of the ex-ante perceived uncertainty is not confirmed by the ex-post fundamentals and that media reports subjective and error-prone opinions, it is plausible to expect that media-based measures of uncertainty are also closely related to noise (Black, 1986; Doms & Morin, 2004; Kaplanski & Levy, 2017). By definition, noise, in the sense of Black (1986), is constituted by informational content related to both uncertainty and sentiment. Thus, it is possible that measurements for noise can be extracted from IEM and EPU.

As expected, noise measures are useful for testing sentiment or noise traders models in capital market. Future researches may also engage in methods to purge (orthogonalize) the economic fundamentals from candidate measures, extracting the components that are more sensitive to subjective aspects and errors of information content for noise proxy construction.

Inserting these variables into predictive models, including versions expunged from the fundamentals, can generate better forecasts, considering that historical series such as stock prices, investment, demand, inflation, consumer and business confidence, inter alia, are manifestations of human behavior (Rambaccussing & Kwiatkowski, 2020).

Better forecasts and parameter estimation help reduce errors in financial management, allowing better investment decisions, with more accurate asset pricing (Baker & Wurgler, 2007; 2012), and decisions on the proportion of liquid assets to be held by companies facing expected inflation (Kumar, 2020).

Another important practical implication of the findings obtained here is the fact that media-based measures for uncertainty can be used as an indicator of the degree of informaticity of public information. That is, they inform the moment to allocate greater attention and effort to obtaining relevant information by agents, with the advantage that this type of nudge, by triggering rational and deliberative thinking, is well accepted by people (Sunstein, 2016). Therefore, it contributes to the literature on nudge and choice architecture.

Specifically, the cost of inattention, which occurs as a result of unwanted results of erroneous expectations and decisions, is influenced by two effects: (a) informational noise: greater uncertainty implies greater noise, as well as greater difficulty in separating information and noise; and (b) irrationality effect (or inattention effect): high uncertainty is associated with the greater weight of heuristics and biases in the process of expectations formation and decisions. Therefore, changes in ex-ante uncertainty can increase the probability of errors in the formation of expectations and decisions. In this context, the value of information increases.

Thus, ex-ante uncertainty indicators can act as a signaling to adjust the effort and attention to obtaining information by consumers, investors, companies, and policy makers. Adjusting the perceived value of information would help calibrate the cost-effectiveness of the effort to obtain and process information (Sims, 2003). Therefore, these indicators can act as a nudge, promoting greater rationality in the process of forming expectations and decision-making.

Finally, this article also contributes to the literature on nudge and choice architecture in a way that ex-ante uncertainty measures or noise can act as control variables for nudging models tests, since there is greater effectiveness of nudges when people are more subject to inattention or to irrationality (Löfgren & Nordblom, 2020).

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