Research article

The impact of uncertainty on business cycles in Brazil♦

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Abstract

The literature on the determinants of short-run fluctuations in economic activity abound but attempts to account for the role of uncertainty only emerged after the Great Recession. Increasing uncertainty slows down economic activity as precautionary behavior leads companies to delay investment plans and households to postpone consumption. This paper evaluates the importance of uncertainty to short-run fluctuations in the Brazilian economy. Using monthly data from 1996 to 2023 and relying on several proxies for uncertainty, the article estimates models based on the generalized method of moments, which controls the possibility of endogeneity. The results indicate that increases in uncertainty – particularly that associated with financial markets' instability – weaken aggregate demand in Brazil.

Keywords

Uncertainty, Business Cycles, GMM.

O impacto da incerteza nos ciclos econômicos do Brasil

Resumo

Os determinantes das flutuações de curto prazo na atividade econômica tem sido objeto de estudo de uma vasta literatura, mas tentativas de avaliar a importância da incerteza somente tornaram-se evidentes após a Grande Recessão. Elevações na incerteza induzem um comportamento cauteloso nos agentes econômicos, levando as firmas a postergarem planos de investimento e os consumidores a adiarem o consumo. Este artigo busca averiguar a relevância da incerteza para as flutuações de curto prazo da economia brasileira. Utilizando dados mensais entre 1996 e 2023, e considerando indicadores alternativos de incerteza, o artigo estima modelos com base no método generalizado dos momentos, que permite lidar com a possibilidade de endogeneidade. Os resultados indicam que elevações na incerteza – particularmente aquela associada à instabilidade no mercado financeiro – enfraquece a demanda agregada no Brasil.

Palavras-chave

Incerteza, Ciclos Econômicos, GMM.

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1. Introduction

Since the Great Recession, macroeconomics literature has increasingly focused on the importance of financial imperfections and uncertainty to fluctuations in economic activity. Several works have analyzed the link between uncertainty and business cycles, but there is yet no consensus on the definition of uncertainty, its measurement, and the direction of causality.

Recent works commonly define uncertainty as second-moment shocks or shocks to the variance of a variable, as opposed to shocks to levels or first-moment shocks considered as drivers of fluctuations in economic activity by the early business cycles literature (e.g. shocks to productivity, preferences, tax rates). These studies model uncertainty as the time-varying volatility of exogenous disturbances (e.g. Bloom 2009; Fernandez-Villaverde et al 2011).

Alternatively, uncertainty has also been modeled as the subjective expectation of future second moments (Benhabib et al 2015; Chatterjee and Milani 2020): here, shocks to beliefs lead to increased perceived uncertainty of future events. This latter definition allows uncertainty to be possibly endogenous (Bachmann and Moscarini 2011; Bachmann et al 2013).

Uncertainty about the future is pervasive during recessions. In uncertain times, precautionary behavior leads to delays in consumption and investment. This effect may be amplified by the presence of financial frictions and adjustment costs to investment. Yet, negative exogenous shocks to economic fundamentals also increase uncertainty. Understanding the interplay between the slowdown in economic activity and uncertainty is fundamental to policy initiatives aimed at fostering stability. The theoretical literature has identified several channels through which uncertainty compromises economic outcomes, but efforts are still required to assess the empirical relevance of these mechanisms.

The present paper evaluates the impact of uncertainty on business cycles in Brazil. Using time-series monthly data between 1996 and 2023, econometric estimations based on the generalized method of moments (GMM) were carried out using different proxies for uncertainty and alternative measures of economic activity. This method addresses the endogeneity issue possibly associated with uncertainty and other factors that influence short-run fluctuations in economic activity. The empirical strategy is validated by a theoretical framework that links uncertainty to fluctuations in aggregate demand.

The present paper aims to contribute to the literature that addresses the issue of causality between uncertainty and aggregate demand fluctuations. A thorough search of the literature has found no related work applying GMM to gauge the importance of uncertainty to business cycles (only Baker et al (2024) have relied on instrumental variables, IV). Using GMM is also novel among studies of the impact of uncertainty on fluctuations in economic activity in Brazil, as the use of VAR models has prevailed (e.g. Costa Filho 2014; Barboza and Zilberman 2018).

Another contribution of the present study is the derivation of an uncertainty indicator that may be used to anticipate recessions and for guiding stabilization policies. This paper uses dynamic factor analysis to estimate the latent factor leading to comovement among different proxies for uncertainty suggested by the literature. Overall, the estimated regressions indicate that increases in the exogenous component of uncertainty slow down aggregate demand. The results also show that proxies for perceived uncertainty seem more relevant than other commonly used uncertainty measures.

Besides this introduction, the paper has six other sections. The second section reviews the literature that links uncertainty to fluctuations in economic activity. The third section describes the theoretical framework underlying the paper's empirical strategy, while the fourth section presents the econometric methodology. The fifth section describes the data and variables, the sixth section examines the estimations' results, and the last section concludes.

2. Uncertainty and business cycles: brief literature review

Recessions are often associated with times of increased uncertainty. The literature has identified several channels through which increases in uncertainty affect aggregate demand by influencing households' consumption and allocation of wealth across different financial assets, and firms' optimal size and investment decisions. Yet, there is no consensus on whether uncertainty shocks lead to recessions or the other way around.

In uncertain times, the possibility of lower future income causes households to behave cautiously. If individuals are risk-averse, mean-preserving increases in the distribution of consumption reduce expected utility. Fernandez-Villaverde and Guérron-Quintana (2020) show that risk-averse economic agents try to prevent large fluctuations in marginal utility by increasing buffer-stock savings. Thus, precautionary behavior causes households to postpone consumption when uncertainty shocks increase the variance of other economic disturbances, such as productivity innovations, demand shifts, and changes in economic policy.

In addition, aggregate demand becomes more responsive to increases in uncertainty when risk-averse agents may allocate their wealth to a variety of assets besides physical capital. Fernandez-Villaverde et al (2011) point out that uncertainty shocks in domestic financial markets may cause resources to shift toward international assets. As a result, credit supply shrinks, hindering fixed capital investment in the home country.

Uncertainty shocks also influence firms' incentives to invest, pricing decisions, and optimal size. For example, the presence of non-convex adjustment costs raises the sensitivity of investment to uncertainty shocks. Bloom (2009) shows that if firms follow Ss rules in their investment decisions due to adjustment costs, the real option value of inaction increases when uncertainty is high, and fewer firms choose to engage in investment activities.

The presence of asymmetric information in financial markets also amplifies the impact of uncertainty shocks on investment. Christiano et al (2014) and Gilchrist et al (2014) show that greater idiosyncratic uncertainty increases the external finance premium, compromising firms' ability to finance the acquisition of raw capital and slowing down investment. Moreover, Arellano et al (2019) argue that financial frictions restrict the availability of insurance. Hiring inputs for production is risky, as firms' expenditures with inputs' acquisition occur before the sale of output. Thus, restricted access to insurance leads firms to self-insure by keeping a buffer stock of unused credit and by reducing investment and employment.

In addition to real frictions, nominal rigidity also causes uncertainty shocks to elicit significant contractions in aggregate demand. According to Fernandez-Villaverde et al (2015), the dispersion of possible ex-post relative prices increases when uncertainty rises. In the presence of price rigidity, the profit function becomes asymmetric with respect to relative prices: if prices are set too low ex-post, firms may have to meet a significant volume of sales at an unfavorable price; if prices are set too high ex-post, higher margins compensate for lower sales. Thus, firms are inclined to set their prices too high, which reduces aggregate demand.

Firms may also endogenously adjust their optimal size in response to uncertainty shocks (the Oi-Hartman-Abel effect). In the presence of decreasing returns to scale, the concavity of the production function ensures that firms increase their profits by reducing their size in the face of negative shocks and by expanding it when good news arrives. In such a context, uncertainty shocks would be expansionary. However, Basu and Bundick (2017) indicate that this effect disappears if adjustment costs to investment are sizeable or prices are sticky. As pointed out before, price rigidity causes firms to choose higher markups when experiencing uncertainty shocks, thereby reducing aggregate demand.

Finally, notice that uncertainty shocks are largely one-sided. Negative productivity shocks, natural disasters, or political shocks increase the likelihood of a recession, but positive innovations do not necessarily mean a higher probability of a boom. Salgado et al (2019) argue that when uncertainty is defined as a negative shock to the skewness of firms' productivity growth, precautionary behavior causes firms to delay investment.

Empirical studies based on VAR models point out that uncertainty shocks increase stock market volatility, and lower investment, employment, consumption, and output. In a preeminent study, Bloom (2009) specified a dummy variable to capture uncertainty shocks hitting the American economy. The variable took the value of one whenever the hp-detrended stock market volatility rose significantly above the mean[1]. The author showed that these volatility shocks lead to short-run contractions and long-run overshots in industrial production and employment.

Carrière-Swallow and Céspedes (2013) showed that emerging economies experience stronger impacts from uncertainty shocks, probably because of less developed financial markets. Using the volatility implied by a synthetic 30-day option on the S&P stock index (VXO) as a measure of uncertainty[2], these authors found that the drop in investment and

[1] Bloom (2009) assured the representativeness of this variable by showing that stock market volatility is strongly linked to demand and productivity uncertainty based on firm-level cross-sectional data.

[2] Following Bloom (2009), they identified uncertainty shocks as periods in which the hp-detrended VXO series exceeded its mean value by more than 1.65 standard deviations.

consumption following uncertainty shocks is much more pronounced in emerging economies than in developed countries.

Gilchrist et al (2014) also found that uncertainty shocks elicit more relevant output responses when associated with a tightening of financial markets' conditions. These authors estimated VAR models using firm-level and aggregated data from the American economy. Their proxy for uncertainty was defined as common shocks to the idiosyncratic volatility of publicly traded companies' equity returns.

The use of indicators based on stock market data captures not only unforeseeable changes in economic fundamentals but also heterogeneity in the cyclicality of firms' business activities and loadings of common risk factors (Jurado et al 2015). Thus, these indicators' volatility may vary even when there is no change in uncertainty. Jurado et al (2015) suggest identifying a measure of macroeconomic volatility that is associated with the common variation in uncertainty across many series, sectors, markets, and geographical regions. Based on a factor-augmented VAR model, these authors show that uncertainty shocks are infrequent, but when these shocks occur, they are often large in magnitude and persistent.

Indicators based on stock market data also suffer from endogeneity bias because these measures may be responding to changes in economic activity rather than causing them. Baker et al (2016) derived three proxies for uncertainty: the number of words related to policy uncertainty that appears in newspaper articles; the number of federal tax code provisions set to expire in future years (a proxy for policy uncertainty); and the standard deviation of financial analysts' forecasts of the future economic outlook. Still relying on a VAR framework and using firm-level panel data and aggregate data from 12 major economies, their estimations indicate that uncertainty rises steeply in recessions. Applying the same econometric strategy but relying on American firms' data, Bloom et al (2018) also reached similar results.

Previously discussed works assumed that uncertainty reflects idiosyncratic shocks to economic fundamentals. Yet, recessions may increase uncertainty as relations and practices among firms, their employees, and their consumers become compromised. For instance, Bachmann and Moscarini (2011) show that recessions dampen firms' profits, encouraging them to adopt riskier, more aggressive pricing strategies to survive.

As risky behavior becomes more prevalent, cross-section dispersion and time-series volatility of economic outcomes increase. These are commonly used measures of uncertainty.

Chatterjee and Milani (2020) point to another reason recessions lead to heightened uncertainty. These authors argue that endogenous changes in confidence about future outcomes arise when beliefs respond to structural shocks. For instance, an aggregate demand shock endogenously changes the uncertainty underlying expected future production because it generates dispersion in beliefs about future realizations of output growth.

Finally, Ludvigson et al (2021) indicate other channels through which recessions may cause greater uncertainty rather than the reverse. For example, a slowdown in economic activity reduces available information, which impairs economic agents' decision-making effectiveness and their ability to forecast the future. Moreover, governments tend to experiment and adopt unfamiliar economic policies during recessions, which also weakens agents' ability to forecast future economic activity. Lastly, recessions lead to the misallocation of capital across firms and generate uncertainty in consumption growth.

Previously discussed estimations based on timing for identification within a VAR framework often ignore that the contemporaneous movement of uncertainty indicators and macro variables bring significant identification challenges, because recursive structures imply that some variables respond to others with a lag (Ludvigson et al 2021; Baker et al 2024). Using standard time-series restrictions to identify exogenous changes in uncertainty is inappropriate because the first and second moments of uncertainty proxies are highly correlated.

A variety of strategies have been used to consider the possibility of endogeneity. Bachman et al (2013) suggest using survey data because it captures the mindset of actual decision-makers. These authors use disagreements in business expectations as a measure of uncertainty but still rely on VAR models. Their estimations indicate that the impact of uncertainty on economic activity is short-lived and minor, while negative long-run shocks to fundamentals increase uncertainty.

Using IV is an alternative strategy to deal directly with endogeneity. If instruments are adequately chosen, IV methods provide consistent parameter estimates, correct bias related to omitted variables and simultaneity, and help provide causal estimates from observational data (Baum et al 2003, 2007) [3]. Baker et al (2024) use the dispersion of individual firms' returns and aggregated stock market volatility as measures of uncertainty, instrumenting them with news shocks related to natural disasters, terrorist attacks, and political shocks. Using cross-country panel data, the authors show that output drops significantly in response to increased uncertainty.

Ludvigson et al (2021) isolate macroeconomic uncertainty from financial uncertainty and force their effects to be orthogonal. Based on data from the American economy, their estimation of VAR models shows that financial uncertainty depresses economic activity, but macroeconomic uncertainty endogenously responds to other contractionary shocks.

More recently, randomized control trials (RCT) in survey data have also been used to avoid the endogeneity problem (Kumar et al 2023; Coibion 2024)[4]. For example, Coibion et al (2024) applied RCT in a survey conducted with consumers in six European countries. They found that household spending on durable goods, services, and non-essential goods reduces in response to an exogenous variation in macroeconomic uncertainty. Bloom et al (2022) also favored the use of survey data as a source of less biased measures of perceived uncertainty. Using data from 25,000 manufacturing plants in the United States, they found that growing uncertainty is highly associated with decreases in investment, employment, and sales.

2.1. Uncertainty and Fluctuations in Economic Activity in Brazil

Previous works analyzing the impact of uncertainty on business cycles in Brazil have relied on standard or Bayesian VARs under some predetermined Cholesky ordering, without resorting to IV or RCT. This section provides a brief overview of this literature.

[3] A variable is considered a good instrument when it is strongly correlated with the explanatory variable believed to be endogenous and uncorrelated with the dependent variable.

[4] These studies are conducted in three stages. First, randomly selected households or firms receive information related to professionals' forecasts of aggregate economic outlook, while others receive no information at all. The proxy for uncertainty is defined as the differences in these economic agents' first and second moment expectations about the future. At a future date, information about these agents' decisions is gathered in a new wave of interviews (e.g. consumers' savings decisions or firms' price setting, employment and investment). At the final stage, the link between uncertainty and economic agents' decisions is established.

Like other empirical studies based on emerging markets data[5], estimations based on Brazilian data point out that uncertainty shocks elicit significant contractions in production, investment, and consumption. For example, Costa Filho (2014) considered three indicators of uncertainty: how frequently the word uncertainty appears in news media; the standard deviation of economic growth forecasts; and the volatility of the stock market index. His results indicated that uncertainty shocks lead to sizeable contractions in industrial production and consumer confidence, but employment is hardly affected.

Barboza and Zilberman (2018) in turn considered not only the impact of domestic uncertainty on economic activity but also external uncertainty shocks. These authors used six different domestic uncertainty indicators: the number of newspaper articles related to uncertainty and related terms; the implicit volatility of exchange rates' option contracts; the volatility of the stock market index; the standard deviation of inflation forecasts; the first principal component obtained from the previous indicators; and an index of economic uncertainty. Barboza and Zilberman (2018) also used the first principal component of an economic policy uncertainty index of countries with whom Brazil has relevant commercial ties to proxy for external uncertainty. Their estimations show that domestic uncertainty shocks slow down industrial production and investment, but external uncertainty shocks are less representative.

More recently, two other works analyzed the role of uncertainty in the Brazilian economy. Melo and Silva (2019) developed a Dynamic Stochastic General Equilibrium (DSGE) model calibrated with Brazilian data and estimated impulse-response functions based on a Bayesian VAR framework. Their estimations point out that uncertainty shocks reduce consumption and increase labor supply.

The present paper uses a more comprehensive set of proxies for uncertainty than the existing studies which analyze uncertainty shocks in the context of the Brazilian economy. In addition, this research employs dynamic factor analysis to derive a comprehensive indicator of uncertainty, while previous studies have resorted to principal component analysis (PCA). The dynamic factor model (DFM) considers the autocorrelation present in the original data and the derived factor. According to Stock and Watson (2016), DFM is more efficient in dealing with time series data than PCA.

[5] See, for example, Carrière-Swallow and Céspedes (2013) and Choi (2018).

Finally, this paper relies on GMM models which explicitly internalize the endogeneity present in the relationship between uncertainty and recessions. GMM considers information contained in time-series data to obtain instruments for endogenous variables. Since business cycles exhibit persistence, lagged values of endogenous variables emerge as viable instruments because they are unrelated to current shocks (Diebold and Rudebusch 1989; Ascari et al 2021).

Theoretically, persistence is justifiable by the presence of sticky information, price and wage rigidities, consumption habits, and financial frictions (Mankiw and Reis 2002; Christiano et al 2005; Gilchrist et al 2009). The next section formally provides the theoretical background for this paper's empirical strategy.

3. Theoretical framework underlying the empirical strategy

Modern business cycles analysis frequently relies on New Keynesian DSGE models. Based on this literature, the present section defines an equilibrium equation for aggregate demand which embodies the role of uncertainty as well as other key elements, such as consumption habits, investment decisions, financial frictions, fiscal policy, and external trade.

Equation (1) represents the log-linearized equilibrium condition for aggregate demand at time t:

$$\tilde{y}_t = c_y \tilde{c}_t + i_y \tilde{\imath}_t + g_y \tilde{g}_t + nx_y \widetilde{nx}_t + u_t^{AD} \tag{1}$$

where $\tilde{y}_t, \tilde{c}_t, \tilde{\imath}_t, \tilde{g}_t$ and $\widetilde{nx}_t$ indicate the deviations of output, consumption, investment, government spending, and trade balance from their steady--state values. The parameters c_y, i_y, g_y and nx_y indicate the steady-state values of consumption, investment, government spending, and trade balance to output ratios, respectively. The variable u_t^{AD} represents idiosyncratic aggregate demand disturbances.

The following subsections describe intertemporal Euler equations for optimal consumption and investment, as well as the feedback rule overseeing government spending, the trade balance, and the link between expectations' formation and uncertainty.

3.1. The Consumption Euler Equation

Macroeconomic variables exhibit a high degree of persistence. Usually, theoretical models incorporate this feature by assuming consumption habits or price rigidity. If drastic changes in consumption are costly, past consumption choices influence current preferences (Christiano et al 2005; Ascari et al 2021). The presence of price rigidity ensures that current inflation responds not only to expected future prices and supply shocks, but also to past inflation (Gali et al, 2005). The present paper presumes the existence of consumer habits.

Households obtain utility from consumption and disutility from work. The representative household wishes to maximize the following expected utility function:

$$E_t \sum_{t=o}^{\infty} \beta^t [U(C_t) - V(L_t)] \tag{2}$$

E_t is the expectational parameter, β is the discount rate ($0 < \beta < 1$). As in Fuhrer (2000), the consumption index, C_t, is defined as:

$$U(C_t) = \frac{(C_t / C_{t-1}^{\Phi})^{1-\theta}}{(1-\theta)} \tag{3}$$

where Φ represents the importance of lagged consumption (the habit reference level) relative to current consumption, and θ is the coefficient of absolute risk aversion (θ > 0). Equation (3) implies that households aim at smoothing both consumption levels and changes in consumption[6]. Finally, the disutility from work is defined as $V(L_t) = (B/\gamma)L_t^{\gamma}$, where L_t is the labor supply, B > 0 and γ > 1.

Assume that consumers acquire goods in both domestic and international markets. To take international transactions into account, the consumption index, C_t, is defined as proposed by Gali and Monacelli (2005):

$$C_t = \left[(1-\zeta)^{\frac{1}{\xi}} \left(C_{H,t}\right)^{\frac{\xi-1}{\xi}} + \zeta^{\frac{1}{\xi}} \left(C_{F,t}\right)^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}} \tag{4}$$

where $C_{H,t}$ is an index of home-produced goods, $C_{F,t}$ is an index of foreign-produced goods, ζ represents the share of imported goods in

[6] Notice that $U(C_t) = \frac{\left(C_t / C_{t-1}^{\Phi}\right)^{1-\theta}}{(1-\theta)} = \frac{1}{(1-\theta)} \left(\frac{C_t}{C_{t-1}} C_{t-1}^{1-\Phi}\right)^{1-\theta}$.

consumption, and ξ indicates the elasticity of substitution between home and foreign goods ($\xi > 1$).

The price index is the weighted average of domestic and foreign goods' prices, with the weights given by $(1 - \zeta)$ and ζ, respectively. If the purchasing-power-parity condition holds, log-linearizing the price index around its steady-state yields $\tilde{p}_t \equiv (1-\zeta)\tilde{p}_{H,t} + \zeta\tilde{p}_{F,t}$, where $p_{H,t}$ and $p_{F,t}$ represent the natural logarithm of the domestic and foreign goods' price indices.

The nominal exchange rate with each trading country and the price of each transacted good in foreign currency influence $p_{F,t}$. Thus, define $\tilde{p}_{F,t} \equiv \tilde{e}_t + \tilde{p}_t^*$, where e_t is the nominal exchange rate, and p_t^* is the average international prices. If the effective terms of trade are defined as $\tilde{x}_t \equiv \tilde{p}_{F,t} - \tilde{p}_{H,t}$, then $\tilde{x}_t = \tilde{e}_t + \tilde{p}_t^* - \tilde{p}_{H,t}$.

The real effective exchange rate, J_t, is equal to the nominal exchange rate times the ratio of international to domestic prices. Thus, the log-linearized real exchange rate around its steady state becomes $\tilde{J}_t = \tilde{e}_t + \tilde{p}_t^* - \tilde{p}_t$. Substituting the previously defined expressions for $\tilde{p}_t$ and $\tilde{x}_t$ on $\tilde{J}_t$ yields the following equation:

$$\tilde{J}_t = (1-\zeta)\tilde{x}_t \tag{5}$$

Given equations (2) to (5), households' optimizing intertemporal consumption choice yields the Euler equation for consumption in a small open economy (Further and Rudebush 2004; Gali and Monacelli 2005):

$$\tilde{c}_t = E_t\tilde{c}_{t+1} - \frac{1}{\theta}(\tilde{r}_t - E_t\tilde{\pi}_{t+1}) + \sum_{i=1}^{I}\tau_i\tilde{c}_{t-i} - \frac{\zeta\epsilon}{\theta(1-\zeta)}E_t\Delta\tilde{J}_{t+1} + u_t^C \tag{6}$$

where r_t is the nominal interest rate; π_t is the inflation rate, which is defined as $\pi_t \equiv p_t - p_{t-1}$; τ_i captures the degree of persistence in consumption, such that $\tau_i > 0$; $\epsilon \equiv \theta\eta_X + (1-\zeta)(\theta\xi - 1) > 0$, and η_X is the degree of substitutability between goods produced in different countries. The term u_t^C represents exogenous consumption preferences shocks ($u_t^C = \rho_C u_{t-1}^C + \varepsilon_t^C, -1 < \rho_C < 1$).

At this point, it is useful to establish a connection between consumption and income. Similar to Mankiw and Campbell (1989) and Fuhrer (2000), assume that a fraction Ψ of the consumers adopt the rule of thumb that their current consumption equals to current income (hand-to-mouth consumers). The remaining consumers behave according to the permanent income hypothesis.

Thus, the change in aggregate consumption in a period t, ΔC_t, equals to $[\Psi \Delta Y_t + (1-\Psi)\Theta_t]$, where Θ_t represents unforecastable changes in the permanent income. Mankiw and Campbell (1989) suggest using log-linearization as an approximation of the true model, which implies that $\tilde{c}_t = \Psi\tilde{y}_t + (1-\Psi)\widetilde{\Theta}_t$. As a result, equation (6) becomes:

$$\tilde{c}_t = E_t\tilde{y}_{t+1} - \frac{1}{\theta}(\tilde{r}_t - E_t\tilde{\pi}_{t+1}) + \Psi\sum_{i=1}^{I}\tau_i\tilde{y}_{t-i} + (1-\Psi)\tilde{Z}_t - \frac{\zeta\epsilon}{\theta(1-\zeta)}E_t\Delta\tilde{j}_{t+1} + u_t^C \quad (7)$$

where $E_t\widetilde{\Theta}_{t+1} = 0$, and $\tilde{Z}_t$ reflects the impact of past unexpected changes in permanent income, such that $\tilde{Z}_t = \sum_{i=1}^{I}\tau_i\widetilde{\Theta}_{t-i}$.

3.2. The Investment Euler Equation

At each period t, financially constrained firms need to choose the optimal investment and stock of capital to be used in $t+1$. The presence of financial markets' imperfections implies that relying on external financing is more costly than using firms' net worth. The derivation of the investment Euler equation in this section primarily relies on the financial accelerator model (Bernanke et al 1998; Gilchrist et al 2009).

The capital stock and the net worth are the state variables. Aggregate capital stock evolves according to the equation:

$$K_{t+1} = \varphi\left(\frac{I_t}{K_t}\right)K_t + (1-\delta)K_t \quad (8)$$

The first term, $\varphi\left(\frac{I_t}{K_t}\right)K_t$, represents the aggregate investment, I_t, where $\varphi(\cdot)$ denotes the presence of increasing marginal adjustment costs ($\varphi'(\cdot) > 0, \varphi"(\cdot) \leq 0$, and $\varphi(0) = 0$). Log-linearizing equation (8) around the steady-state yields the evolution of the capital stock: $\tilde{k}_{t+1} = \delta\tilde{\imath}_t + (1-\delta)\tilde{k}_t$.

The optimal investment condition implies that the price of a unit of capital is given by $Q_t = \dfrac{1}{\varphi'(I_t/K_t)}$. Log-linearizing this expression around the steady-state yields:

$$\left(\tilde{\imath}_t - \tilde{k}_t\right) = \eta \tilde{q}_t \tag{9}$$

where $\eta = \frac{\varphi"(I_t/K_t)}{\varphi'(I_t/K_t)}$. Equation (9) represents the link between investment and the value of installed assets.

Entrepreneurs receive the proceeds from investing in fixed capital and resell it for Q_{t+1}, after accounting for depreciation. Thus, the return on capital depends on the marginal product of capital and on the gains from reselling fixed capital. Gilchrist et al (2009) demonstrate that the expression for the log-linearized return on capital around the steady-state is given by:

$$E_t \tilde{r}_{t+1}^k = (1-\psi) E_t \widetilde{mpk}_{t+1} + \psi E_t \tilde{q}_{t+1} - \tilde{q}_t \tag{10}$$

where r_{t+1}^k is the realized gross rate of return on capital at time $t+1$, $\psi = (1-\delta)/[R_K^* + (1-\delta)]$, and R_K^* is the steady-state rate of return on capital.

The acquisition of capital stock for period $t+1$ is financed by the entrepreneur's net worth (N_t) and loans backed by households' savings (B_t). Since $Q_t K_{t+1} = B_t + N_t$, then the entrepreneur's leverage grows as the ratio $(N_t/Q_t K_{t+1})$ decreases. The presence of financial markets' imperfections implies that the external finance premium may be defined as the ratio of $E_t r_{t+1}^k$ and the real risk-free interest rate $(r_t - E_t \pi_{t+1})$, $S_t \equiv \frac{E_t r_{t+1}^k}{(r_t - E_t \pi_{t+1})}$. When $Q_t K_{t+1} < N_t$, $B_t = 0$, $E_t r_{t+1}^k = r_t - E_t \pi_{t+1}$ and $S_t = 1$. If $Q_t K_{t+1} > N_t$, external financing is required: $S_t = s\left(\frac{N_t}{Q_t K_{t+1}}\right)$, such that $s'(\cdot) < 0$.

The log-linearized external finance premium around the steady state may be defined as $\tilde{s}_t = E_t \tilde{r}_{t+1}^k + \left(\tilde{r}_t - E_t \tilde{\pi}_{t+1}\right)$. Alternatively,

$$\tilde{s}_t = -\chi\left[\tilde{n}_t - \left(\tilde{q}_t + \tilde{k}_{t+1}\right)\right] + u_t^s \tag{11}$$

where χ represents the elasticity of the premium with respect to the entrepreneur's leverage, $\chi > 0$; and u_t^s denotes the exogenous disturbances to the credit supply process $(u_t^S = \rho_S u_{t-1}^S + \varepsilon_t^I, -1 < \rho_S < 1)$. When firms' leverage increases, the external finance premium rises and, consequently, investment decreases. Thus, in the presence of asymmetric information, the external finance premium responds inversely to changes in net worth relative to the size of the desired capital stock.

Assume that current net worth is determined not only by the current return on capital but also by past net worth. Gilchrist et al (2009) obtain the following expression for the log-linearized net worth:

$$\tilde{n}_t = \frac{K}{N}\tilde{r}_t^k + \left(\frac{K}{N} - 1\right)(\tilde{s}_{t-1} + \tilde{r}_{t-1}^*) + \omega\tilde{n}_{t-1} + u_t^{nw} \tag{12}$$

where (K/N) represents the steady-state ratio of capital expenditures to net worth, ω is the survival rate of entrepreneurs, and u_t^{nw}proxies for exogenous shocks to the values of assets used as collateral $(u_t^{nw} = \rho_{nw}u_{t-1}^{nw} + \varepsilon_t^{nw}, -1 < \rho_{nw} < 1)$.

Gilchrist et al (2009) derive the following Euler equation for optimal investment:

$$\tilde{\imath}_t - I_1\tilde{\imath}_{t-1} - I_2E_t\tilde{\imath}_{t+1} = I_3\tilde{q}_t \tag{13}$$

where $I_1 = \frac{1}{1+\beta a^{(1-\sigma_C)}}$, $I_2 = \frac{\beta a^{(1-\sigma_C)}}{1+\beta a^{(1-\sigma_C)}}$, and $I_3 = \frac{1}{1+\beta a^{(1-\sigma_C)}}\frac{1}{a\varphi^2}$. The intertemporal elasticity of consumption and the trend growth rate of technology are represented by σ_C and a, respectively. The parameters β and σ_C depict households' savings preferences, while the parameter a captures the influence of technology shocks on income growth.

The investment Euler equation shows how the weighted average of past, present, and expected future investment depends on the value of installed capital, $\tilde{q}_t$. Re-arranging equation (10) shows that $\tilde{q}_t$ responds positively to $E_t\widetilde{mpk}_{t+1}$ and to $E_t\tilde{q}_{t+1}$, but reacts negatively to $E_t\tilde{r}_{t+1}^k$. Since $E_t\tilde{r}_{t+1}^k = \tilde{s}_t - (\tilde{r}_t - E_t\tilde{\pi}_{t+1})$, increases in the external finance premium reduce investment through its impact on $\tilde{q}_t$. Thus, investment is tightly linked to $\tilde{q}_t$ and $\tilde{s}_t$.

3.3. The Government Spending Feedback Rule

Government spending may be incorporated into the model through fiscal rules, distortionary taxation, or endogenous changes in government expenditures. Assume that government spending is fully financed with lump-sum taxes and follows the following feedback rule (Fevé et al 2013):

$$G_t = \bar{g}\left(\frac{Y_t}{Y_{t-1}}\right)^{-\kappa_G} e^{u_t^G} \tag{14}$$

where $\bar{g}$ is a factor scale for steady-state government expenditures; κ_G represents the elasticity of government spending with respect to production growth ($\kappa_G \geq 0$); and u_t^G represents discretionary spending shocks.

Log-linearizing equation (14) around its steady-state yields:

$$\tilde{g}_t = -\kappa_G(\tilde{y}_t - \tilde{y}_{t-1}) + u_t^G \tag{15}$$

$$u_t^G = \rho_G u_{t-1}^G + \varepsilon_t^G, -1 < \rho_G < 1 \tag{16}$$

Equation (15) implies that fluctuations in government spending have a countercyclical endogenous component, represented by the impact of output growth on spending, and an exogenous component represented by u_t^G (discretionary changes in fiscal policy).

Fevé et al (2013) assume that consumers' utility depends on the acquisition of private and public goods, such that $C_t = C_t^P + \alpha_g G_t$. The parameter α_g Indicates whether government spending substitutes or complements consumption: if $\alpha_g < 0$, G_t complements consumption; if $\alpha_g \geq 0$, G_t is a substitute for consumption. Complete crowding-out occurs when $\alpha_g = 1$, while G_t operates through a negative income effect on labor supply when $\alpha_g = 0$.

In such a setting, the impact of $\tilde{g}_t$ on $\tilde{y}_t$ depends not only on g_y, but also on the steady-state government spending multiplier, $\frac{\Delta y}{\Delta g} = \frac{1-\alpha_G}{1+\nu[1-g_y(1-\alpha_G)]}$. The multiplier decreases with increases in α_g, which indicates that public and private consumption become more substitutable (stronger crowding out effect). Thus, the impact of $\tilde{g}_t$ on $\tilde{y}_t$ is given by μ_G:

$$\mu_G \equiv g_y \frac{\Delta y}{\Delta g} = g_y \frac{1-\alpha_G}{1+\nu\big[1-g_y(1-\alpha_G)\big]} \tag{17}$$

Equations (15) through (17) show that government spending affects aggregate demand through three channels: the degree of complementarity/substitutability between private consumption and government spending; the countercyclical endogenous component of government spending; and discretionary fiscal policy shocks. A high degree of complementarity between private and public consumption increases μ_G amplifying the correlation between $\tilde{g}_t$ on $\tilde{y}_t$, since more public spending leads to greater private consumption.

3.4. Trade Balance

For simplicity, assume complete markets at the international level, and symmetric preferences across countries, such that the optimal intertemporal consumption choice must be held for the representative household in any other country. Based on these assumptions, Gali and Monacelli (2005) derive a simple relationship between domestic consumption, world consumption, and the terms of trade given by $\tilde{c}_t = \tilde{c}_t^* + \left(\frac{1-\zeta}{\theta}\right)\tilde{x}_t$. The variable $\tilde{c}_t^*$ is an index of world consumption, θ and ζ represent the coefficient of absolute risk aversion and the share of imported goods, respectively.

In equilibrium, aggregate domestic production equals the domestic and world consumption of home-produced goods. Gali and Monacelli (2005) demonstrate that aggregate domestic production around the steady is given by:

$$\tilde{y}_t = \tilde{c}_t + \frac{\epsilon\zeta}{\theta}\tilde{x}_t \tag{18}$$

The trade balance is defined as domestic production minus the domestic consumption of home-produced goods and the domestic consumption of foreign goods. Thus,

$$\widetilde{nx}_t \equiv \tilde{y}_t - \tilde{c}_t - \zeta\tilde{x}_t \tag{19}$$

Substituting (5) and (18) into (19) yields the following expression for the trade balance:

$$\widetilde{nx}_t = \frac{\zeta}{(1-\zeta)}\left(\frac{\epsilon\zeta}{\sigma} - 1\right)\tilde{J}_t \tag{20}$$

Equation (20) implies that the sign of the relationship between the real exchange rate and the trade balance is ambiguous. Increases in the real exchange rate lead to increases in the trade balance only if $\frac{\epsilon\zeta}{\sigma} > 1$.

3.5. Expectations Formation and Uncertainty

The present paper incorporates uncertainty into the model by defining how agents form their expectations. For simplicity, assume that consumption persistence is captured well enough by consumption in the previous period, such that $\tau_1 = \tau$ and $\tau_i = 0$ for any $i > 1$. Then, plugging equations

(7), (13), (15), (17), and (20) in equation (1) yields the expression for the short-run fluctuations in aggregate demand:

$$\begin{aligned}\tilde{y}_t = {} & \frac{c_y \tau\Psi + \mu_G \kappa_G}{1+\mu_G\kappa_G}\tilde{y}_{t-1} \\ & + \frac{c_y}{1+\mu_G\kappa_G}\left[E_t\tilde{y}_{t+1} - \frac{1}{\theta}(\tilde{r}_t - E_t\tilde{\pi}_{t+1}) + (1-\Psi)\tilde{Z}_t \right. \\ & \left. - \frac{\zeta\epsilon}{\theta(1-\zeta)}E_t\Delta\tilde{j}_{t+1}\right] + \frac{i_y}{1+\mu_G\kappa_G}[I_1\tilde{\imath}_{t-1} + I_2E_t\tilde{\imath}_{t+1} + I_3\tilde{q}_t] \\ & + \frac{nx_y}{1+\mu_G\kappa_G}\left[\frac{\zeta}{(1-\zeta)}\left(\frac{\epsilon\zeta}{\sigma}-1\right)\tilde{j}_t\right] + u_t^{AD}\end{aligned} \tag{21}$$

where $u_t^{AD} = \dfrac{1}{1+\mu_G\kappa_G}\{c_y u_t^C + \mu_G u_t^G + i_y[(1/\chi)u_t^s + u_t^{nw}]\}$.

Equation (21) shows that expectations of future output, inflation, real exchange rate volatility, and investment influence current fluctuations in aggregate demand. Recall that fluctuations in investment are affected by the value of installed capital, which depends on its expected future value[7]. Thus, agents need to establish the values of $E_t\tilde{y}_{t+1}$, $E_t\tilde{\pi}_{t+1}$, $E_t\Delta\tilde{j}_{t+1}$ and $E_t\tilde{q}_{t+1}$. For ease of exposition, define Λ_{t+1} as a proxy for the economic environment at $t+1$, such that $E_t\Lambda_{t+1} \equiv \frac{c_y}{1+\mu_G\kappa_G}\left[E_t\tilde{y}_{t+1} + \frac{1}{\theta}E_t\tilde{\pi}_{t+1} - \frac{\zeta\epsilon}{\theta(1-\zeta)}E_t\Delta\tilde{j}_{t+1}\right] + \frac{i_y}{1+\mu_G\kappa_G}E_t\tilde{q}_{t+1}$.

Assume that agents form their beliefs about the economy by using an asymmetric loss function which weighs negative and positive forecast errors differently (Benhabib et al 2015; Chatterjee and Milani 2020). Using an asymmetric loss function implies that overprediction of certain variables may be more costly because it could lead to inaction and greater losses. In such circumstances, Chatterjee and Milani (2020) show that optimal forecasts depend on the conditional expectation and the conditional variance.

Thus, the optimal forecast of Λ_{t+1} would be given by:

$$\hat{\Lambda}_{t+1} = \hat{E}_t\Lambda_{t+1} + \frac{d}{2}\hat{E}_t\sigma^2_{\Lambda,t+1} \tag{22}$$

[7] The variable $\tilde{q}_t$ also depends on $E_t\widetilde{mpk}_{t+1}$ and $E_t\tilde{r}^k_{t+1}$. The latter depends on $\tilde{s}_t$, and $(\tilde{r}_t - E_t\tilde{\pi}_{t+1})$.

where $\hat{E}_t \Lambda_{t+1}$ represents the mean forecast of Λ_{t+1}; $\hat{E}_t \sigma^2_{\Lambda,t+1}$ is the expected variance; and $\hat{E}_t$ represents subjective expectations. The term $\hat{E}_t \sigma^2_{\Lambda,t+1}$ proxies for agents' *ex-ante* perceived uncertainty, while its importance is given by the degree of asymmetry, d. When $d < 0$, positive forecast errors are more costly than negative forecast errors, while the reverse applies if $d > 0$. If $d = 0$, positive and negative forecast errors have similar weights.

Agents learn about key relationships among variables by observing historical data and by considering their perceived uncertainty. They form their expectations according to a perceived law of motion (PLM), which Chatterjee and Milani (2020) define as:

$$\hat{\Lambda}_t = \mathrm{A} + \mathrm{B}\hat{\Lambda}_{t-1} + C u^{AD}_{t-1} + D\hat{E}_t \sigma^2_{\Lambda,t+1} + \epsilon_{1,t} \quad (23)$$

Equation (23) implies that agents learn about the endogenous variables' steady-state values through A, while B illustrates the dynamic relationship, C shows how $\hat{\Lambda}_t$ reacts to past exogenous disturbances, and D indicates how agents react to their perceived uncertainty. The term $\epsilon_{1,t}$ represents exogenous shocks to the learning process.

Agents also need to learn about the dynamics of perceived uncertainty. Thus, a similar PLM applies to the estimated uncertainty:

$$\sigma^2_{\Lambda,t+1} = A^* + B^* \hat{\Lambda}_{t-1} + C^* u^{AD}_{t-1} + \epsilon_{2,t} \quad (24)$$

where the parameters A^*, B^*, and C^* indicate that learning about uncertainty is influenced by the realized macroeconomic environment and recent shocks. Equation (25) allows perceived uncertainty to be partially endogenous, which is consistent with Bachman and Moscarini (2011) and Bachman et al (2013).

The PLMs described by equations (23) and (24) indicate that agents form their expectations based on data up to $t - 1$, which implies that information is only available with a lag. Taking the subjective expectation of equations (23) and (24) shows how expectations evolve L periods forward, where L indicates how far ahead uncertainty is observable:

$$\hat{E}_t \hat{\Lambda}_{t+L} = \hat{A}_{t-1} + \hat{B}_{t-1} \hat{E}_t \hat{\Lambda}_{t+L-1} + \hat{C}_{t-1} \hat{E}_t u^{AD}_{t+L-1} + \hat{D}_{t-1} \hat{E}_t \sigma^2_{\Lambda,t+L+1} + \epsilon_{1,t} \quad (25)$$

$$\hat{E} \sigma^2_{\Lambda,t+L} = \hat{A}^*_{t-1} + \hat{B}^*_{t-1} \hat{\Lambda}_{t-1} + \hat{C}^*_{t-1} u^{AD}_{t-1} + \epsilon_{2,t} \quad (26)$$

3.6. Some Simplifying Assumptions and Inferences

Given the expectations' formation defined in the previous section, replacing $E_t\Lambda_{t+1}$ by $\hat{E}_t\hat{\Lambda}_{t+1}$ in equation (21) yields the final aggregate demand specification to be estimated by the empirical model:

$$\tilde{y}_t = \frac{c_y\tau\Psi + \mu_G\kappa_G}{1+\mu_G\kappa_G}\tilde{y}_{t-1} + \frac{c_y}{1+\mu_G\kappa_G}\left[(1-\Psi)\tilde{Z}_t - \frac{1}{\theta}\tilde{r}_t\right] + \frac{i_y}{1+\mu_G\kappa_G}[I_1\tilde{\imath}_{t-1} + I_3\tilde{q}_t] + nx_y\left[\frac{\zeta}{(1-\zeta)}\left(\frac{\epsilon\zeta}{\sigma}-1\right)\tilde{J}_t\right] + \hat{E}_t\hat{\Lambda}_{t+1} + u_t^{AD} \quad (27)$$

where $\hat{E}_t\hat{\Lambda}_{t+1}$ is defined according to equations (25) and (26). The remainder of this section provides inferences regarding the expected signs and magnitudes of the coefficients estimated by the empirical exercise. It also justifies some additional simplifying assumptions.

While persistence implies that the coefficient of $\tilde{y}_{t-1}$ is positive, dynamic stability requires that it lies between zero and unit (i.e. $0 < \frac{c_y\tau\Psi+\mu_G\kappa_G}{1+\mu_G\kappa_G} < 1$ or $c_y\tau\Psi < 1$). Regarding the impact of interest rates on aggregate demand, the estimated coefficient lies in the range of negative one and zero, because estimations of consumer models indicate large values for θ (Romer, 2020). Thus, $\frac{c_y}{\theta(1+\mu_G\kappa_G)} > 0$ and $c_y < \theta(1+\mu_G\kappa_G)$.

The present paper assumes that most consumers follow the rule-of-thumb behavior ($\Psi \cong 1$) and the impact of $\tilde{Z}_t$ on aggregate demand is negligible. There is lack of evidence on consumption smoothing in the literature, which often cites liquidity restrictions, impatience, limited attention, limited planning, and other behavioral traits as reasons for rule-of-thumb behavior (Carroll et al, 2020).

Regarding investment, the empirical exercise uses the external finance premium and the value of installed capital to account for the impact of investment on aggregate demand. Investment is expected to contract in response to increases in the premium and to contractions in the value of capital. This strategy was also adopted by Ng and Schaller (1996), who point out that both variables reflect the agency costs of financial intermediation and directly influence investment spending. In addition, Altavilla et al (2024) have recently shed light on the importance of the external finance premium and balance-sheet vulnerabilities for firms' investments. This route was taken because of the lack of monthly data for investment.

As pointed out before, the impact of changes in real exchange rates on aggregate demand is uncertain, as it depends on whether $\frac{\epsilon\zeta}{\sigma} < 1$. Previous works have emphasized this ambiguous effect: increases in exchange rates may exert inflationary pressures, slowing down economic activity; however, exchange rates' depreciation stimulates net exports, which increases aggregate demand. To avoid such ambiguity, the empirical estimations evaluate the impact of real exchange rate volatility, which is unambiguous: greater exchange rate volatility leads to suboptimal allocation of resources and distortions in relative prices, which hinders external trade and international financial transactions (Moslares and Ekanayake 2018).

Regarding uncertainty, the present research assumes that uncertainty is a proxy for agents' expectations about the future: greater uncertainty implies dim prospects about future outcomes. Thus, past expectations about the economy and past exogenous shocks, which appear in equation (25), are considered of minor importance relative to uncertainty. These elements are only considered indirectly, as equation (26) implies that uncertainty is an endogenous variable influenced by past expectations and exogenous shocks[8].

Finally, the empirical exercise presumes that uncertainty slows down consumption and investment by influencing agents' assessment of their future income and business prospects. Thus, the empirical analysis uses an indicator of uncertainty that encompasses an overall measure of macroeconomic uncertainty as a proxy for $\hat{E}_t\hat{\Lambda}_{t+1}$, as discussed in section 5.

4. Econometric model

The GMM model has been commonly used to estimate Euler equations (e.g. Hansen et al 1996; Gali et al 2005; Ascari et al 2021). The orthogonality conditions assume that the residuals are not correlated with variables that are predetermined at time t, allowing the latter to be used as instruments.

The econometric model estimates the following equation:

$$\tilde{y} = X\beta + u \tag{28}$$

[8] While uncertainty shocks slow down aggregate demand, the empirical evidence also suggests that agents become less confident in predicting the future during recessions (e.g. Bloom et al 2014).

where $\tilde{y}$ is a n x 1 vector representing the cyclical component of the aggregate demand indicator, and n is the number of observations; X is a n x k matrix with k explanatory variables; and the n x 1 vector u represents the error term.

Assuming that $E[X/u] \neq 0$, X may be partitioned into $[X_1 \quad X_2]$ such that X_1 represents a matrix with K_1 endogenous variables, while X_2 is a matrix of K_2 exogenous variables. Then, equation (28) can be re-written as:

$$\tilde{y} = [X_1 \quad X_2][\beta_1 \quad \beta_2]' + u \tag{29}$$

X_1 includes the following variables: the lagged dependent variable, $\tilde{y}_{t-1}$; the indicator of perceived uncertainty, $\hat{E}_t\hat{\Lambda}_{t+1}$; the cyclical component of the real interest rate ($\tilde{r}_t$); the cyclical component of the government spending ($\tilde{g}_t$); the cyclical component of the external finance premium ($\tilde{s}_t$); the cyclical component of the value of assets ($\tilde{q}_t$); and the volatility of the real exchange rate ($\tilde{j}_t$). The vector X_2 represents the dummy variable that accounts for the shift from an exchange rate to an inflation target monetary policy regime (d_{flex}).

Let $Z = [Z_1 \quad Z_2]$ be an $n\,x\,L$ matrix of instruments. If the instruments are exogenous, then $E[Z/u] = 0$. Define the L_1 instruments in Z_1 as the excluded instruments, and the L_2 instrument in Z_2 as the included instrument ($L_2 \equiv L - L_1$, and $Z_2 \equiv X_2$). Thus, the excluded instruments are the instruments for the endogenous variables, while the included instrument is the exogenous variable itself.

Given the sample length and the number of endogenous variables, the present study uses two lags of each endogenous variable as instruments in Z_1[9]. Thus, the matrix $L_1 \equiv [X_{1,t-1} \quad X_{1,t-2}]$, where $X_{1,t-1}$ and $X_{1,t-2}$ represent the matrices of the first and second lags of the variables in X_1. The exogenous variable, d_{flex}, appears in its current value as the only included instrument ($Z_2 \equiv d_{flex}$). Since there are more instruments than endogenous variables, the estimated model is overidentified.

Hansen et al (1996) point out that a set of L instruments generates a set of L moments given by the expression:

$$g_i(\beta) = Z'_i u_i = Z'_i(\tilde{y} - X_i\beta) \tag{30}$$

[9] Reliable data for most time-series variables in Brazil is available after 1996, which restricts the sample size. In addition, almost all explanatory variables are presumed endogenous. Thus, the inclusion of more than two lags of X_1 would lead to the proliferation of instruments, which could severely bias the results (Baum 2003). Using only one lag, on the other hand, would not capture the persistence present in business cycles data and would turn the GMM estimator into an IV estimator.

where g_i is a L x 1 matrix and i = 1, 2, …, n. Instruments' exogeneity requires that $E[g_i(\beta)] = 0$. The GMM estimator identifies a vector $\hat{\beta}$ such that $\bar{g}(\hat{\beta}) = 0$, where $\bar{g}(\hat{\beta}) = \frac{1}{n}\sum_{i=1}^{n} g_i(\beta)$. If the model is overidentified, it is not possible to identify a single $\hat{\beta}$ that sets all L moment conditions to zero. Then, a L x L weighting matrix W is used to construct a quadratic form of the moment conditions, which yields the estimator's objective function $J(\widehat{\beta}) = n\bar{g}(\widehat{\beta})'W\bar{g}(\widehat{\beta})$. The GMM estimator is represented by the vector $\hat{\beta}$ that minimizes this objective function:

$$\hat{\beta}_{GMM} \equiv \arg\min_{\widehat{\beta}} J(\hat{\beta}) = n\bar{g}(\hat{\beta})'W\bar{g}(\hat{\beta}) \tag{31}$$

According to Baum et al (2007), the GMM estimator is consistent for any symmetric positive definite weighting matrix. However, when the model is overidentified, the choice of W affects the estimated value of $\hat{\beta}$. Moreover, efficiency requires that W minimizes the asymptotic variance of the estimator, S. Baum et al (2007) show that the optimal weighting matrix is given by $W = S^{-1}$.

In the two-step efficient GMM estimator (GMM2S), an estimate of the matrix S is obtained in the first step. The two-stage least squares (2SLS) estimator is used to obtain consistent estimates of β and of the sample residuals. Then, these estimated sample residuals are used to obtain the estimate of the covariance estimator, $\hat{S} = \frac{1}{n}(Z'\hat{\Omega}Z)$, where $\widehat{\Omega}$ is the diagonal matrix of the squared residuals. Baum et al (2007) point out that $\widehat{S}$ may be consistently estimated using an Eicker–Huber–White heteroscedasticity robust covariance estimator.

In the second step, GMM2S calculates $\widehat{W} = \widehat{S}^{-1}$, and treats $\widehat{W}$ as a constant matrix. Using $\widehat{W}$ in Equation (36) yields $\hat{\beta}_{GMM2S}$:

$$\hat{\beta}_{GMM2S} \equiv \arg\min_{\widehat{\beta}} J(\hat{\beta}) = n\bar{g}(\hat{\beta})' \left(S(\tilde{\beta})\right)^{-1} \bar{g}(\hat{\beta}) \tag{32}$$

where $\tilde{\beta}$ and $(S(\tilde{\beta}))^{-1}$ represent the consistent estimates of β and of the covariance estimator obtained in the first step, whereas $\bar{g}(\hat{\beta})$ is derived from the second-step residuals.

According to Baum et al (2003), the optimal weighting matrix is a function of fourth moments. Thus, reasonable estimates of $\widehat{W}$ may require large sample sizes. When the errors in u are conditionally homoscedastic, the

2SLS estimator should be preferred over the GMM estimator. However, in the presence of heteroscedasticity, the GMM estimator is more efficient.

The efficient GMM2S estimator may be extended to account for residuals' autocorrelation. When $E[g_t g'_{t-1}] \neq 0$, the heteroscedastic- and autocorrelation-consistent (HAC) estimate of S is defined as $\hat{S} = \Gamma_0 + \sum_{j=1}^{q}(\hat{\Gamma}_j + \hat{\Gamma}'_j)$, where $\hat{\Gamma}_j = \frac{1}{n}\sum_{t=1}^{n-j}(Z'_t \hat{u}_t \hat{u}_{t-j} Z_{t-j})$. According to Baum (2007), inserting autocovariance from 1 to n into this summation implies that the sample orthogonality conditions, $\hat{g}_i$, tend to infinity with the sample size. Instead, many studies have set $(n-j)$ = the number of nonzero autocorrelations. Yet, Newey and West (1987) argue that this information may be unknown, or autocorrelation may not be finite.

Newey and West (1994) suggest that the summation in $\hat{\Gamma}_j$ is truncated at a specified lag. The authors set $\hat{S} = \Gamma_0 + \sum_{j=1}^{q} k\left(\frac{j}{q_n}\right)(\hat{\Gamma}_j + \hat{\Gamma}'_j)$, where $k\left(\frac{j}{q_n}\right)$ is a Bartlett kernel function, and q_n is the selected bandwidth or truncation lag. This kernel function is widely used in empirical studies, and it performs well among alternative estimators (Kolokotrones et al 2024).

While different kernel functions often produce similar estimation results, the choice of bandwidth may significantly influence the size of test statistics. The bandwidth may be defined as an increasing function of n. For instance, Andrews (1991) shows that $q_n = O(n^{1/3})$ minimizes the asymptotic mean squared error of the Bartlett kernel function. Alternatively, Newey and West (1994) derive an optimal bandwidth selection criterion given by $q_n = \left[\breve{\gamma}\left(n^{1/3}\right)\right]$, where [·] denotes "the integer part of", and the parameter $\breve{\gamma}$ is obtained according to an asymptotically optimal procedure[10].

The present paper uses three different bandwidths and relies on the specification tests described below to identify which one provides more robust results. Besides the Newey and West (1994) optimal bandwidth criterion and Andrews' (1991) suggestion of $q_n = O(n^{1/3}) \cong 7$, the estimations also consider the rule-of-thumb bandwidth of $q_n = 12$ based on the assumptions that (i) autocorrelation in monthly data typically dies out between the 6th and the 12th lag, and (ii) longer lags produce smaller bias (Baum et al 2007; Sun et al 2008).

[10] See Newey and West (1994) for a detailed description of how $\breve{\gamma}$ is derived.

Hansen et al (1996) have shown that GMM2S exhibits poor finite sample properties. These authors suggest the use of an alternative estimator known as the continuously updated estimator (GMM-CUE). Different from the GMM2S estimator, which takes the weighting matrix as a constant matrix, the covariance matrix estimated by GMM-CUE is modified continuously as the value of β changes in the minimization problem indicated by equation (31). Using numerical methods, the weighting matrix and β are chosen simultaneously such that the residuals in S are the same residuals in $\bar{g}$:

$$\hat{\beta}_{GMM2S} \equiv \arg\min_{\hat{\beta}} J(\hat{\beta}) = n\bar{g}(\hat{\beta})' \left(S(\hat{\beta})\right)^{-1} \bar{g}(\hat{\beta}) \tag{33}$$

Solving Equation (33) relies on the generalization of a limited information maximum likelihood estimator, which uses IV or GMM2S estimates as starting values.

When GMM-CUE converges, it has the best small sample properties among the GMM estimators. Based on Monte Carlo experiments, Hansen et al (1996) show that GMM-CUE has the following advantages: more reliable hypothesis testing and confidence intervals, parameter estimates with smaller median bias, and more robust estimates of tests for overidentifying restrictions. In addition, GMM-CUE is invariant to data transformations and normalizations. Thus, although section 6 presents the results based on estimations using GMM2S in addition to estimations based on GMM-CUE, the outcomes based on the latter strategy are considered more robust because of the small data sample used here.

4.1. Diagnostics

All equations were initially estimated using 2SLS under the assumption of independent and identically distributed errors (*i.i.d.*). Then, a few tests were conducted to verify the presence of autocorrelation and heteroscedasticity (see Baum et al 2003). Cumby-Huizinga test results rejected the null hypothesis of no autocorrelation of the residuals in all estimations. Moreover, four different tests for the null hypothesis of homoscedasticity also indicated the presence of heteroscedasticity in all estimations: the Pagan-Hall test, the Pagan-Hall test with assumed normality, the White-Koenker test and the Breusch-Pagan/Godfrey/Cook-Weisberg test[11].

[11] For conciseness, only the results of the commonly used White-Koenker test are displayed in section 6.

Thus, these preliminary evaluations signaled the need to use the GMM estimator with HAC standard errors. In the context of GMM estimations, four specification tests are usually used to ensure the robustness of the results: instruments' validity, instruments' explanatory power, instruments' weakness, and weak identification.

The GMM estimator assumes that the population moment conditions have mean zero, or $E[Z/u] = 0$. The first specification test investigates if the instruments are unrelated to the dependent variable. Under the null hypothesis of joint instruments' validity, the value of J in equation (36) has a χ^2 distribution with (L – K) degrees of freedom. This is known as the Hansen J-statistic test.

The second specification test verifies the explanatory power of the instruments. A set of instruments is considered informative if $E[Z/X_1] \neq 0$. In the absence of correlation between the instruments and the endogenous variables, the estimated coefficients become biased: IV becomes inconsistent and exhibits larger mean squared errors than ordinary least squares.

For equation (33) to be estimated, the model needs to be identified. Not only the order condition $L \geq K$ must be satisfied, but also the matrix $Q_{XZ} \equiv E(X_i' Z_i)$ needs to be of full column rank K. Given that $L_1, K_1 \geq 1$, let r_i represent the canonical correlation between the linear combination of the K_1 columns in X_1 and the linear combination of the L_1 columns in Z_1, where $i = 1, \ldots, K_1$. Baum et al (2007) show that the rank condition is satisfied when all K_1 canonical correlations are significantly different from zero. If one or more of these correlations are zero, the model is underidentified.

Different tests have been developed to test the null hypothesis of underidentification, such as the Anderson Lagrange-multiplier (LM) test, the Cragg-Donald statistic, and the Kleibergen-Paap statistic. The Anderson LM test verifies the null hypothesis that the smallest canonical correlation is zero, while the Cragg-Donald statistic represents a Wald test with a similar null hypothesis. Because these two tests are only valid if the errors are *i.i.d.*, the present paper presents the results of the Kleibergen-Paap LM test statistic, which is a robust version of the Anderson LM test (Baum et al 2007).

The weak instruments problem arises when the correlations between the instruments and the endogenous variables are non-zero but small. Thus, testing solely for underidentification is not enough, particularly because Staiger and Stock (1997) have shown that the weak instrument problem may arise even when the correlations between X and Z are significant at the conventional levels. According to Baum et al (2007), the difference between the underidentification tests discussed previously and the weak instruments test is solely related to finite sample adjustment and critical values. The author also states that GMM-CUE is more robust to weak instruments than 2SLS and GMM2S.

The usual weak instruments test is based on the Cragg-Donald F statistic. Yet, this test is only valid if the errors are $i.i.d$. Thus, in the presence of autocorrelation and heteroscedasticity, Staiger and Stock (1997) suggest a rule of thumb that if the Kleibergen-Paap Wald F statistic is greater than ten, the weak instruments problem is ruled out. Ascari et al (2021) point out that estimations of Euler equations for production and consumption are prone to suffer from the weak instruments' problem. Thus, the results of this specification test are especially relevant for the present paper.

The final specification test verifies the joint significance of the endogenous variables. The null hypothesis of the Anderson-Rubin weak-identification test is that the coefficients of the endogenous variables are jointly equal to zero. Baum et al (2003) indicate that this test is robust to the presence of weak instruments.

5. Empirical analysis: data and variables

The paper uses monthly data from the Brazilian economy between January 1996 and April 2023 obtained from BCB (2023), unless otherwise noted[12]. This section initially describes the measures of aggregate demand ($\tilde{y}$) used as dependent variables. Afterwards, it presents the alternative proxies for uncertainty, $\hat{E}_t\hat{\Lambda}_{t+1}$, and the results of the dynamic factor analysis. Lastly, the section details the other determinants of aggregate demand.

[12] This period of analysis was chosen due to data availability.

5.1. Measures of Aggregate Demand

The cyclical components of four aggregate demand indicators were alternatively used as dependent variables: the gross domestic product, the Brazilian Central Bank's index of economic activity, industrial production, and employment ($\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{y}}_{\boldsymbol{GDP}}, \tilde{\boldsymbol{y}}_{\boldsymbol{IBC}}, \tilde{\boldsymbol{y}}_{\boldsymbol{IND}}$ **or** $\tilde{\boldsymbol{y}}_{\boldsymbol{EMP}}$)[13]. The real GDP is represented by its cumulative value over the past 12 months[14], while the IBC and IND are seasonally adjusted indexes, and EMP is the seasonally adjusted number of employees of the public and private sectors.

To obtain the cyclical components, three alternative filters were used on the natural logarithm of the aggregate demand variables: the two-sided HP filter, the one-sided HP filter, and the CF filter. The early literature on business cycles commonly used the two-sided filter proposed by Hodrick and Prescott (1997). Yet, this filter was often criticized because it produces spurious relations and presents end-of-sample bias (Hamilton 2018).

The one-sided HP filter is in turn solved recursively. This filter assumes that only current and past states influence the current observation. Thus, the backward nature of DSGE models suggests the one-sided HP filter is preferred to its two-sided counterpart.

Filters with greater precision often cause losses in degrees of freedom (Baxter and King 1999; Hamilton 2018). Using these filters poses a problem to the present study because of restrictions in data availability for Brazil. Besides the HP filters, this paper used the band-pass filter proposed by Christiano and Fitzgerald (2003), which shows greater efficiency than the HP filters, particularly when using monthly data, without losses in degrees of freedom.

5.2. Measures of Uncertainty

Three different strategies are commonly undertaken to measure uncertainty (Fernandez-Villaverde and Guérron-Quintana, 2020): (i) using likelihood-based models to estimate the stochastic volatility processes for the variables of interest; (ii) using text mining to identify the frequency of events related to economic uncertainty; and (iii) conducting surveys with economic agents to derive measures of subjective uncertainty.

[13] The IBC anticipates the GDP results by aggregating the monthly production of the agriculture, industry, and service sectors.

[14] The consumer price index (IPCA) is used to calculate the real GDP, since there is no monthly deflator data.

Jurado et al (2015) claim that all these strategies have shortcomings. Time-varying volatility may reflect changes in risk aversion and other reasons unrelated to uncertainty about economic fundamentals. Alternatively, using cross-sectional dispersion in individual stocks' data to proxy for uncertainty also has potential flaws: the dispersion in firms' returns, sales, and productivity may be due to heterogeneity in loadings of common risk factors or in the cyclicality of firms' business activities. Finally, disagreements in survey forecasts may reflect differences in opinion, biases due to pecuniary reasons, or omission of relevant information.

Jurado et al (2015) also point out that using a single indicator fails to recognize that macroeconomic uncertainty should reflect the common variation across many series. To address some of these issues and ensure robustness, this paper relies on a variety of uncertainty indicators. The first set of indicators is related to the financial markets:

- **EMBI**: the Emerging Markets Bond Index Plus reflects the difference in the daily performance of Brazilian government bonds compared to the performance of the US Treasury bonds (IPEADATA 2023). The variable indicates foreign investors' perception of risk by capturing changes in the country's fundamentals and international liquidity shocks' spillovers. EMBI represents the monthly standard deviation of the daily index.

- **VIX**: the CBOE volatility index is a measure of the 30-day expected volatility of the US stock market (CBOE 2023). This index is obtained by aggregating the weighted prices of the S&P 500 index put and call options over a wide range of strike prices and is widely used as an indicator of global financial markets' uncertainty shocks. The variable VIX is calculated as the average daily volatility in each month.

- **VOLB3**: this variable represents the standard deviation of the Brazilian stock-market daily returns in each month. Stock market volatility is a commonly used proxy for uncertainty in financial markets (Bloom 2009; Caldara 2016).

- **DY_1**: changes in stock-market returns' volatility arise from changes in real fundamental volatility and uncertainty shocks (Diebold and Yilmaz 2008). A measure of uncertainty may be obtained from a two-step procedure. First, GDP and stock-market returns' growth rates are separately fit into AR(3) models. The absolute values of the residuals of each regression are retained as proxies for conditional fundamental and conditional stock market volatilities. Then, conditional stock market volatility is regressed on conditional fundamental volatility. DY_1 represents the residuals of this latter regression.

- **DY_2**: Diebold and Yilmaz (2008) also suggest regressing unconditional stock volatility on unconditional fundamental volatility. Unconditional fundamental and stock market volatilities are defined as the standard deviation of the GDP and stock market returns' growth rates over the past 12 months. DY_2 represents the residuals of this regression.

Besides financial variables, some works suggest using the volatility of macroeconomic variables to proxy for uncertainty. This second set of uncertainty indicators includes:

- **VOLGY**: Bloom (2014) uses the volatility of GDP's growth rate as a proxy for macroeconomic uncertainty. VOLGY is the standard deviation of these growth rates over the past 12 months.
- **VOLINF**: price volatility increases in uncertain times. VOLINF represents the standard deviation of inflation rates over the past four months (Bachmann and Moscarini 2011).
- **VOLTFP**: the volatility of growth rates in total factor productivity (TFP) is also used as a measure of macroeconomic uncertainty (Bloom 2018). Assuming a constant-returns-to-scale Cobb-Douglas production function, $TFP_t = Y_t / K_t^{\alpha} L_t^{1-\alpha}$. VOLTFP is the standard deviation of TFP's growth rates over the past 12 months[15].

The final set of uncertainty indicators is based on (i) text mining of news media publications for the incidence of terms related to uncertainty (e.g. Baker et al 2016)[16]; or (ii) surveys with economic agents to assess the dispersion in their forecasts of economic indicators. These variables are the best available proxies for perceived uncertainty. The estimations include the detrended values of the natural logarithm of the following indices:

[15] Short-run variation in the capital stock is considered negligible (Karras and Song 1996). As estimated by Bender Filho (2017), the present paper assumes $(1 - \alpha)$ to be 0,65.
[16] Text mining consists of using specific software to count the number of times certain words appear in selected media archives in a certain period and using this information to build an index.

- **WUI**: the world uncertainty index is the ratio of the number of times the word "uncertainty" appears in the Economist Intelligence Unit's country monthly report and the total number of words contained in the report (FRB 2023).

- **EPU**: the economic policy uncertainty index represents how frequently the following words appear in the archives of the Folha de São Paulo (FSP) newspaper: economy or economics, uncertain or uncertainty, and any one of the selected terms associated with the central bank and fiscal policy (Baker et al 2023).

- **IIEBR**: the Brazilian index of economic uncertainty is the weighted average of two other indices, the IIEMID and the IIEEXP (FGV 2023)[17]. **IIEMID** is obtained by text mining the terms uncertainty, instability, and crisis in six Brazilian news outlets (FSP, Estadão, Correio Braziliense, Valor Econômico, Globo e Zero Hora). **IIEEXP** represents the dispersion of experts' forecasts of exchange rates, the Selic, and the inflation rate 12 months forward.

Correlation among these variables is relevant and may be due to common latent factors (see Appendix 1). Thus, estimating a dynamic factor model (DFM) addresses the claim by Jurado et al (2015) that uncertainty reflects common variation across different series. In addition, using such an index fits well with the theoretical framework previously presented, as uncertainty is the key determinant of economic agents' expectations of future economic prospects, $\hat{E}_t\hat{\Lambda}_{t+1}$. Finally, DFM also allows increasing degrees of freedom.

DFM assumes that the synchronized movement of observable variables is driven by latent factors and zero-mean idiosyncratic errors (Stock and Watson 2016). Since all observables are stationary in the present study[18], the estimated model defines the observables as linear functions of an unobserved factor. The model also assumes the unobserved factor follows an AR(2) process and the errors in the equations for the observables are autocorrelated. This strategy yields a constrained VAR model with an unobserved autocorrelated factor.

Since WUI, IIEBR, IIEMID, and IIEEXP have smaller data sets, these variables were evaluated in regressions run separately to preserve degrees of freedom. Table 1 displays the estimated results of the DFM. The Wald

[17] $IIEBR = 0.8 * IIEMID + 0.2 * IIEEXP$.

[18] Unit root tests are available upon request.

test indicates the overall significance of the included variables, while the estimated AR(1) terms point to the presence of autocorrelation among observables, except for DY_1. The estimated factor **(UNCERT)** shows persistence, and it is a good predictor of all but three indicators: VOLINF, VOLGY, and VOLTFP.

Table 1 – Indicator of Uncertainty: Dynamic Factor Model

Factor Estimation			**AR Terms - Observable Variables**			
	Coefficient	p-value	Dep. Var.	Exp. Var.	Coefficient	p-value
$Factor_{t-1}$	0.709***	0.000	-	-	-	-
$Factor_{t-2}$	0.024	0.750	-	-	-	-
embi	14.969***	0.000	e.embi	$(e.embi)_{t-1}$	0.792***	0.000
dy_1	0.023***	0.000	e.dy_1	$(e.dy\_1)_{t-1}$	-0.077	0.241
dy_2	0.004***	0.000	e.dy_2	$(e.dy\_2)_{t-1}$	0.950***	0.000
volb3	10.077***	0.000	e.volb3	$(e.volb3)_{t-1}$	0.947***	0.000
vix	2.726***	0.000	e.vix	$(e.vix)_{t-1}$	0.987***	0.000
volinf	-0.005	0.519	e.volinf	$(e.volinf)_{t-1}$	0.927***	0.000
volgy	-0.00004	0.628	e.volgy	$(e.volgy)_{t-1}$	1.000***	0.000
voltfp	0.00003	0.460	e.voltfp	$(e.voltfp)_{t-1}$	1.000***	0.000
epu	0.104***	0.000	e.epu	$(e.epu)_{t-1}$	0.995***	0.000
Obs.	338	Wald p-value		0.000		

Note: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1 shows how UNCERT has evolved. Notice that the derived latent factor takes negative values in some periods, even though uncertainty has been previously defined as the expected variance of the optimal forecast of future economic activity, $\hat{E}_t \sigma^2_{\Lambda,t+1}$. These negative values arise because two of the indicators used in the estimation of the DFM take positive and negative values: DY_1 and DY_2. This issue does not affect the interpretation of the latent factor, as increases in UNCERT represent greater uncertainty. By inspecting Figure 1, it is evident that UNCERT normally peaks right before or during recession periods, as indicated by the business cycles' chronology defined by CODACE (2023).

In addition, Box 1 lists the periods and events in which UNCERT consistently rose 1.65 standard deviations above its mean, a benchmark defined by Bloom (2009) to identify periods of heightened uncertainty. The chronology largely coincides with the events identified by Costa Filho (2014) as responsible for increased uncertainty in Brazil, but it also incorporates other shocks that hit the Brazilian economy.

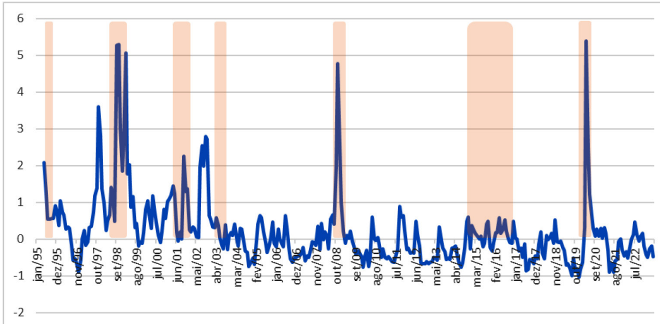

Figure 1 – Indicator of Uncertainty

Note: shadowed bars indicate recessions, according to CODACE (2023).

Box 1 – Periods of Heightened Uncertainty in Brazil

Period	Events
Mar/95 – Jul/96	Mexico currency crisis; fiscal imbalances in Brazil
Jun/97 – Aug/99	Financial crisis in East Asia and Russia; end of the exchange rate targeting regime in Brazil
Jan/00 – May/03	NASDAQ bubble burst; September 11th terrorist attacks; Crisis in Argentina; Lula's first term election
Mar/05 – May/05	Political crisis ("Mensalão")
Jul/08 – Feb/09	Great recession
Sep/11 – Dec/11	Downgrade of the USA sovereign debt, debt crisis in Europe
Oct/14 – Aug/16*	Political crisis ("Lava-Jato"), energy price shocks, and impeachment of Dilma Rousseff
Mar/00 – Aug/00	Covid

Note: the dates were selected as long as UNCERT > 1.65 standard deviations for at least three consecutive months; (*) this period was segmented into three phases: Oct/14 - Feb/15; Sep/15 - Oct/15; and Jun/16 - Aug/16.

5.3. Control Variables

The econometric model includes the cyclical components of the following explanatory variables: government spending ($\tilde{\boldsymbol{g}}_t$), real interest rate ($\tilde{\boldsymbol{r}}_t$), external finance premium ($\tilde{\boldsymbol{s}}_t$), and the value of assets ($\tilde{\boldsymbol{q}}_t$). It also included as explanatory variables the volatility of the real exchange rate ($\tilde{\boldsymbol{j}}_t$) and a dummy variable to control for the shift in monetary policy regime in 1999 ($\boldsymbol{d}_{flex}$). All indicators expressed in real terms were obtained using the IPCA.

Government spending is represented by the accumulated central government real expenditures over the past 12 months (Tesouro Nacional 2023). If fiscal policies are used to stabilize aggregate demand, government spending should be countercyclical. Yet, procyclical government spending is common in emerging markets. This is due to governments' limited access to funding growing expenditures during recessions, or due to competition for rents by political agents during economic booms (Alesina and Tabellini 2005).

Financial market conditions are proxied by the real interest rate, the external finance premium, and the value of assets. The real interest rate is the annualized value of the difference between the Selic rate and the IPCA. The external finance premium reflects the severity of information asymmetry problems and is measured as the annualized values of the difference between the average interest rate charged on business loans and the Selic. The value of assets is measured by the natural logarithm of the seasonally adjusted real value of the companies listed in the B3 stock exchange (B3 2023). Increases in both real interest rates and the external finance premium and lower values of assets signal tight conditions in financial markets.

The real exchange rate volatility is calculated following Moslares e Ekanayake (2018):

$$\tilde{J}_t = \left[\frac{1}{m}\sum_{i=1}^{m}(\ln RER_{t+i-1} - \ln RER_{t+i-2})^2\right]^{0,5} \tag{38}$$

where RER is the real exchange rate index in dollar terms and m = 12. As pointed out previously, greater exchange rate volatility slows down economic activity.

Finally, the estimations included a dummy variable to control for the change in monetary policy regime from exchange rate to inflation rate target, which occurred in the late 1990s. The variable $\boldsymbol{d_{flex}}$ takes the value of zero up to 1998, and the value of one afterwards.

Appendix 2 displays the descriptive statistics and pairwise correlations among the variables used in the estimations. Preliminary evidence indicates that most uncertainty indicators are negatively correlated to the measures of aggregate demand.

6. Estimation results

The first set of estimation results are presented in Table 2. These baseline regressions relied on the CF filter to derive detrended data and used UNCERT as the indicator of uncertainty. Section 6.1 in turn presents the results obtained when (i) using HP-filtered; (ii) substituting UNCERT by the individual proxies for uncertainty included in the DFM; and (iii) replacing UNCERT by indicators of perceived uncertainty.

Table 2 shows the results obtained using both GMM2S and GMM-CUE, adjusted for the presence of heteroscedasticity and autocorrelation. However, the discussion ahead about the economic relevance of the estimated coefficients focuses on the results obtained using GMM-CUE, as this method provides more robust results.

The diagnostic tests indicate that some estimations failed the underidentification test, particularly those based on GMM2S. Yet, none of the estimated equations suffers from the weak instruments' problem, which is of special concern when estimating Euler equations (Ascari et al, 2021). Moreover, the estimations performed well in all other specification tests.

Overall, the results in Table 2 show that rising uncertainty slows down aggregate demand: the coefficient of UNCERT is consistently negative and statistically significant at a 1% level in all estimations, except when $\tilde{y}_t = \tilde{y}_{GDP}$. Regarding the economic relevance of uncertainty, if UNCERT increases by 1 standard deviation, industrial production declines by 1.8%, while the IBC and employment contract by 0.9% and 0.7%, respectively (columns 4, 6 and 8).

Costa Filho (2014) and Barboza and Zilberman (2018) also find that employment and the IBC respond less than industrial production to increases in uncertainty. However, the estimated impact of uncertainty on all three variables is more sizable in the present study, particularly the decrease in employment (Costa Filho (2014) estimates that the unemployment rate increases by less than 0.05%). The greater sensitivity of industrial production relative to the IBC or the GDP indicates that agriculture and services are less susceptible to fluctuations in uncertainty than fixed capital production (Barboza and Zilberman, 2018; Bloom et al, 2018).

Table 2 also shows that all proxies for aggregate demand exhibit persistence, as indicated by the statistical significance and size of the estimated coefficients of $\tilde{y}_{t-1}$. This finding reinforces the importance of including consumption habits and price inertia in theoretical models. In addition, since these coefficients fall between zero and unity, all models exhibit dynamic stability.

Some other interesting results emerge from these baseline regressions. Among the remaining explanatory variables, only the coefficients of dflex, government spending and the value of assets exhibit statistical significance regardless of the aggregated demand indicator used as the dependent variable. The introduction of the inflation target regime was associated with increases in GDP, but industrial production and employment were affected negatively. The increase in unemployment following the introduction of inflation targeting seems to be a common pattern in developing countries, as pointed out by Fry-McKibbin and Wang (2014).

Aggregate demand is crowded out by increases in government spending. Although there is no consensus in the literature regarding the cyclical behavior of government spending in Brazil, similar evidence has also been found by Gadelha and Divino (2013, 2021). A 10% increase in government expenditures reduces GDP, industrial production, the IBC, and employment by 0.6%, 1.2%, 0.3% and 0.6%, respectively (columns 2, 4, 6 and 8).

Table 2 – Estimation Results: Indicator of Uncertainty Based on Factor Analysis

	$\tilde{y}_t = \tilde{y}_{GDP}$		$\tilde{y}_t = \tilde{y}_{IND}$		$\tilde{y}_t = \tilde{y}_{IBC}$		$\tilde{y}_t = \tilde{y}_{EMP}$	
	(1) GMM2S	(2) CUE	(3) GMM2S	(4) CUE	(5) GMM2S	(6) CUE	(7) GMM2S	(8) CUE
$\tilde{y}_{t-1}$	0.942***	0.975***	0.907***	0.857***	0.914***	0.919***	0.958***	0.842***
	(0.010)	(0.064)	(0.024)	(0.089)	(0.025)	(0.040)	(0.030)	(0.040)
UNCERT	-0.00004	-0.001	-0.002***	-0.018***	-0.002***	-0.009***	-0.001**	-0.007***
	(0.0002)	(0.001)	(0.001)	(0.005)	(0.0003)	(0.002)	(0.0004)	(0.001)
$\tilde{J}_t$	-0.070***	0.237**	0.024	0.116	0.038	0.098	0.018	0.064**
	(0.012)	(0.100)	(0.028)	(0.104)	(0.024)	(0.061)	(0.011)	(0.030)
d_{flex}	0.004***	0.034***	-0.004**	-0.022**	–	–	-0.003**	-0.014***
	(0.001)	(0.012)	(0.002)	(0.010)	–	–	(0.001)	(0.003)
$\tilde{g}_t$	-0.012*	-0.066**	0.008	-0.117***	-0.006	-0.032**	-0.021**	-0.060***
	(0.007)	(0.026)	(0.011)	(0.037)	(0.008)	(0.012)	(0.010)	(0.014)
$\tilde{r}_t$	-0.0001	-0.001	-0.001**	-0.0002	-0.0002	-0.0002	-0.0000	0.0005**
	(0.0001)	(0.001)	(0.0003)	(0.001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
$\tilde{s}_t$	0.00004	-0.002***	0.0003	0.001	0.0001	0.001**	0.0002**	0.0003
	(0.0001)	(0.001)	(0.0003)	(0.001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
$\tilde{q}_t$	0.004	0.008	0.018**	0.065**	0.015***	0.022***	0.009***	0.032***
	(0.002)	(0.009)	(0.008)	(0.027)	(0.003)	(0.0063)	(0.002)	(0.006)
C	-0.001*	-0.043***	0.003	0.016*	-0.001	-0.004*	0.002**	0.011***
	(0.001)	(0.014)	(0.002)	(0.009)	(0.001)	(0.002)	(0.001)	(0.003)
Obs.	326	326	326	326	241	241	326	326
R^2	0.991	0.660	0.974	0.632	0.977	0.902	0.980	0.879
Specification Tests[1]								
C.-Huizinga	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
W./Koenker	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Underident.[2]	0.439	0.101	0.356	0.054	0.204	0.092	0.021	0.021
Weak Inst..[3]	27.695	14.899	21.223	14.691	37.751	32.226	15.071	15.071
Weak Ident.[4]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J-Stat.	0.152	0.752	0.213	0.235	0.113	0.317	0.396	0.709

Notes: detrended data obtained with the CF-filter; robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1); (1) the specification tests' results shown are p-values, except for the weak identification test, which is represented by the F-statistic; (2) Kleibergen-Paap rk LM statistic; (3) Kleibergen-Paap Wald rk F statistic; (4) Anderson-Rubin.

Increases in the value of assets signal less severe information asymmetry problems, which eases lending restrictions and stimulates economic activity (e.g. Bernanke et al, 1998; Gilchrist et al, 2009). The estimations show that if $\tilde{q}_t$ grows by 10%, the industrial production index, the IBC, and employment expand by 0.7%, 0.2%, and 0.3% (Table 2, columns 4, 6, and 8). The value of assets shows no statistically significant relation to GDP.

Surprisingly, the coefficients of the interest rate, the external finance premium, and exchange rate volatility exhibit no regular pattern regarding statistical significance or coefficient signs. This outcome may be due to the high correlation between these variables and the value of assets, leading to multicollinearity issues (appendix 2).

6.1. Alternative Specifications

To verify if the results are sensitive to the type of detrending filter used, the regressions were rerun with HP-filtered data. The results for the estimated coefficients of UNCERT are displayed in Table 3. The statistical significance of the uncertainty indicator's coefficients is limited to the estimations in which $\tilde{\boldsymbol{y}}_{\boldsymbol{t}} = \tilde{\boldsymbol{y}}_{\boldsymbol{IBC}}$: an increase in UNCERT by 1 standard deviation leads to a 0.4% drop in the IBC. Recall, however, that these results should be viewed with caution because the CF filter is considered more efficient (Christiano and Fitzgerald 2003).

The uncertainty variables included in the dynamic factor analysis proxy for financial and macroeconomic uncertainty. Yet, the results displayed in Table 1 indicate that UNCERT is a good predictor for financial uncertainty but does a poor job of predicting macroeconomic uncertainty. To avoid possible biases associated with the factor analysis, the regressions were rerun using each uncertainty proxy separately as a regressor. This strategy also allows for assessing the importance of different sources of uncertainty.

Table 3 – Estimated Coefficients of UNCERT: Using the HP Filters

		$\tilde{y}_t = \tilde{y}_{GDP}$	$\tilde{y}_t = \tilde{y}_{IBC}$	$\tilde{y}_t = \tilde{y}_{IND}$	$\tilde{y}_t = \tilde{y}_{EMP}$
Two-Sided HP Filter	GMM2S	0.0001	-0.004***	-0.002	-0.0004
		(0.0004)	(0.001)	(0.003)	(0.001)
	CUE	0.001**	-0.004***	-0.003	0.0003
		(0.0005)	(0.002)	(0.003)	(0.001)
One-Sided HP Filter	GMM2S	0.0005	-0.004***	-0.003	-0.0004
		(0.0004)	(0.001)	(0.003)	(0.001)
	CUE	0.003	-0.004***	-0.003	-0.0002
		(0.003)	(0.002)	(0.003)	(0.001)

Note: Complete results available upon request; robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

In consonance with Gilchrist et al (2014) and Ludvigson et al (2021), the results in Table 4 underscore the importance of financial uncertainty[19]. The coefficients of four financial volatility variables normally exhibit the expected negative sign and statistical significance: EMBI, VIX, DY_1, and DY_2. However, only the regressions including VIX and DY_2 are considered robust according to all specification tests. None of the macroeconomic uncertainty measures appears to be consistently important to fluctuations in economic activity.

Table 4 – Estimated Coefficients of the Indicators of Uncertainty

	$\tilde{y}_t = \tilde{y}_{GDP}$	$\tilde{y}_t = \tilde{y}_{IND}$	$\tilde{y}_t = \tilde{y}_{IBC}$	$\tilde{y}_t = \tilde{y}_{EMP}$
EMBI	0.001***	-0.0000**	-0.002**	-0.0001**
	(0.0002)	(0.0000)	(0.001)	(0.0000)
VIX	-0.0000	-0.0003**	-0.0001**	-0.0003
	(0.000)	(0.0001)	(0.0000)	(0.0004)
VOLB3	-0.0000	-0.0001	-0.0003***	-0.0001*
	(0.000)	(0.0001)	(0.000)	(0.000)
DY_1	-0.119	-0.448***	-0.192***	-0.146***
	(0.074)	(0.151)	(0.061)	(0.038)
DY_2	-0.106***	0.053	-0.25***	-0.043***
	(0.029)	(0.050)	(0.093)	(0.013)
VOLINF	-0.015	-0.005	0.001	0.006***
	(0.010)	(0.015)	(0.004)	(0.002)
VOLGY	-0.018	-1.389***	7.914	-3.759
	(0.202)	(0.459)	(5.987)	(3.314)
VOLTFP	-0.116	-0.491	-5.217*	-10.149*
	(0.294)	(2.551)	(2.971)	(6.001)
CFEPU	0.016	-0.009	-0.029***	-0.002*
	(0.011)	(0.006)	(0.010)	(0.001)

Notes: results obtained when using the GMM-CUE estimator and CF-filtered data (complete results available upon request); robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The final set of estimations used uncertainty indicators based on (i) text mining of news media for the incidence of uncertainty-related terms, or (ii) surveys which assess the dispersion of economic agents' forecast of eco-

[19] The differences in the coefficients' magnitudes presented in Table 3 occur because these indicators differ significantly in units of measurement (see their mean values in Appendix 1).

nomic activity. These variables proxy for perceived uncertainty, a concept that is directly linked to the theoretical framework in section 3.

Table 5 shows that increases in perceived uncertainty slow down economic activity. This outcome is statistically significant regardless of the aggregate demand indicator used. Industrial production exhibits the greatest response to uncertainty: a rise in the uncertainty indicator by 1 standard deviation causes industrial production to contract up to 11.5% (when the IIEBR proxies for uncertainty). Overall, the diagnostic tests indicate that all results in Table 5 are robust (only two estimations fail the underidentification test, while other tests' results remained satisfactory: when $\tilde{y}_t = \tilde{y}_{EMP}$, and IIEMID or WUI represent uncertainty).

The present paper's empirical exercise highlights the importance of incorporating uncertainty in aggregate demand estimations, particularly financial uncertainty. In addition, the results point out that theoretical advances in the modeling of perceived uncertainty are paramount, as its empirical relevance seems quite robust.

Table 5 – Estimated Coefficients of the Alternative Uncertainty Indicators

	$\tilde{y}_t = \tilde{y}_{GDP}$	$\tilde{y}_t = \tilde{y}_{IND}$	$\tilde{y}_t = \tilde{y}_{IBC}$	$\tilde{y}_t = \tilde{y}_{EMP}$
IIEBR	-0.013***	-0.109***	-0.008	-0.034***
	(0.005)	(0.031)	(0.012)	(0.012)
IIEEXP	-0.008***	0.027*	-0.018***	0.050**
	(0.003)	(0.014)	(0.004)	(0.024)
IIEMID	0.0002	-0.101***	-0.041***	-0.006
	(0.015)	(0.027)	(0.013)	(0.006)
WUI	-0.015**	-0.025***	-0.022***	-0.005***
	(0.006)	(0.007)	(0.004)	(0.020)

Notes: results obtained when using the GMM-CUE estimator and CF-filtered data (complete results available upon request); robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

7. Conclusion

This paper evaluated the role of uncertainty in the Brazilian business cycles after the mid-1990s. The paper uses DFM to derive a latent factor that leads to the comovement of various proxies for uncertainty. This strategy recognizes that macroeconomic uncertainty reflects the common variation across many series (Jurado et al 2015). In addition, DFM is superior to PCA, which has been commonly used in the literature relying on Brazilian data.

Another novel contribution arises from the use of GMM, which controls the possibility that uncertainty is endogenous. This stands in contrast to much of the literature, particularly the analyses of the impact of uncertainty shocks in Brazil, whose favored econometric strategy has been VAR models assuming that uncertainty shocks are exogenous.

The overall result obtained here is that uncertainty indeed slows down economic activity. Most uncertainty indicators' estimated coefficients displayed statistical significance, mainly those related to the financial sector and to perceived uncertainty. In addition, these estimated coefficients are more sizeable than indicated by previous works. Industrial production is particularly affected, indicating that investment is highly sensitive to uncertainty shocks.

These results corroborate the existing literature which underscores the importance of public policies directed at promoting a more stable economic environment. Not only do fiscal and monetary policies need to be sustainable and effective, but they also need to be conveyed transparently to efficiently anchor economic agents' expectations and reduce uncertainty. Furthermore, prudential regulation may also be important to avoid exacerbated risk exposure in financial markets.

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APPENDIX 1 – MEASURES OF UNCERTAINTY: DESCRIPTIVE STATISTICS AND CORRELATIONS

Descriptive Statistics

	EMBI	VIX	VOLB3	DY_1	DY_2	VOLGY	VOLINF	VOLTFP	WUI	EPU	IIEBR	IIEMID	IIEEXP
Obs	341	341	341	338	338	341	341	340	317	341	281	281	257
Mean	25.439	20.193	26.020	-0.002	-0.001	0.007	0.259	0.004	4.803	4.786	4.655	4.645	4.685
Std. Dev.	36.856	7.896	15.433	0.057	0.034	0.015	0.168	0.004	0.505	0.624	0.144	0.128	0.200

Pairwise Correlations

	EMBI	VIX	VOLB3	DY_1	DY_2	VOLGY	VOLINF	VOLTFP	WUI	EPU	IIEBR	IIEMID	IIEEXP
EMBI	1.000												
VIX	0.390	1.000											
VOLB3	0.475	0.619	1.000										
DY_1	0.543	0.321	0.429	1.000									
DY_2	0.487	0.470	0.513	0.367	1.000								
VOLGY	0.203	-0.161	-0.146	0.122	-0.211	1.000							
VOLINF	0.278	0.086	-0.038	0.106	0.135	0.346	1.000						
VOLTFP	0.172	-0.143	-0.117	0.133	-0.177	0.954	0.309	1.000					
WUI	-0.125	0.188	-0.087	-0.062	-0.161	0.160	0.120	-0.282	1.000				
EPU	-0.100	0.125	0.141	-0.042	-0.018	-0.329	-0.151	-0.379	0.607	1.000			
IIEBR	0.133	0.385	0.158	0.116	0.325	0.225	0.243	-0.055	0.723	0.556	1.000		
IIEMID	0.012	0.335	0.160	0.094	0.228	0.179	0.146	-0.094	0.740	0.621	0.963	1.000	
IIEEXP	0.373	0.459	0.176	0.196	0.613	0.327	0.506	0.123	0.478	0.219	0.811	0.618	1.000

APPENDIX 2 – ECONOMETRIC ESTIMATIONS: DESCRIPTIVE STATISTICS AND PAIRWISE CORRELATIONS

	$\tilde{y}_{PIB}$	$\tilde{y}_{IND}$	$\tilde{y}_{IBC}$	$\tilde{y}_{EMP}$	UNCERT	CFWUI	CFIIEBR	CFIIEEXP	CFIIEMID	$\tilde{g}$	$\tilde{r}$	$\tilde{s}$	$\tilde{q}$	$\tilde{j}$
Obs	341	341	245	341	338	317	281	257	281	341	341	341	329	340
Mean	0.003	-0.001	-0.0002	0.0001	0.209	4.803	-0.001	0.005	0.000	-0.004	0.083	-0.098	0.002	0.035
Std. Dev.	0.026	0.032	0.020	0.020	0.956	0.505	0.081	0.135	0.065	0.055	4.227	5.496	0.135	0.019

Pairwise Correlations

	$\tilde{y}_{PIB}$	$\tilde{y}_{IND}$	$\tilde{y}_{IBC}$	$\tilde{y}_{EMP}$	UNCERT	CFWUI	CFIIEBR	CFIIEEXP	CFIIEMID	$\tilde{g}$	$\tilde{r}$	$\tilde{s}$	$\tilde{q}$	$\tilde{j}$
$\tilde{y}_{PIB}$	1.000													
$\tilde{y}_{IND}$	0.062	1.000												
$\tilde{y}_{IBC}$	0.572	0.937	1.000											
$\tilde{y}_{EMP}$	0.259	0.154	0.395	1.000										
UNCERT	-0.019	-0.218	-0.334	-0.133	1.000									
CFWUI	0.063	-0.153	-0.099	0.030	-0.068	1.000								
CFIIEBR	-0.290	-0.735	-0.831	-0.486	0.431	0.182	1.000							
CFIIEEXP	-0.286	-0.418	-0.538	-0.404	0.451	0.115	0.838	1.000						
CFIIEMID	-0.290	-0.806	-0.876	-0.494	0.412	0.163	0.943	0.624	1.000					
$\tilde{g}$	-0.484	0.172	-0.146	-0.743	0.159	-0.050	0.433	0.520	0.350	1.000				
$\tilde{r}$	-0.295	-0.402	-0.291	0.069	0.281	0.118	0.251	0.059	0.262	-0.031	1.000			
$\tilde{s}$	-0.413	-0.425	-0.503	-0.134	0.282	0.066	0.519	0.319	0.510	0.165	0.893	1.000		
$\tilde{q}$	0.240	0.786	0.717	-0.020	-0.302	-0.161	-0.625	-0.352	-0.647	0.044	-0.559	-0.571	1.000	
$\tilde{j}$	-0.491	-0.448	-0.659	-0.250	0.151	0.074	0.707	0.650	0.633	0.230	0.336	0.552	-0.461	1.000

Note: Detrended data obtained with the CF filter (results obtained with other filters are available upon request).

DECLARAÇÃO DE DISPONIBILIDADE DE DADOS

Os dados utilizados neste estudo estão disponíveis mediante solicitação ao autor. Dados adicionais e informações complementares também poderão ser fornecidos para fins de verificação ou replicação. A disponibilização está condicionada à inexistência de restrições de acesso público.

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CONFLITO DE INTERESSE

Os autores declaram não terem quaisquer conflitos de interesse.

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