

Modeling Economic Recessions through Monte Carlo Simulation: A Probabilistic Approach to Uncertainty in Macroeconomic Indicators

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Abstract

The unpredictability of economic recessions represents one of the greatest challenges in contemporary macroeconomics [16, 18]. Events such as the Great Depression, the 2008 financial crisis, and the Covid-19 recession highlight the limitations of traditional forecasting approaches [15, 21]. Standard macroeconomic indicators often fail to provide timely warnings [5, 19]. This study investigates the applicability of *Monte Carlo Simulation* as a statistical tool to model uncertainty and enhance the predictability of downturns [1, 3, 13]. We conduct an exploratory and quantitative case study using leading macroeconomic indicators [7, 8] across two major recessions: the 2008 global financial crisis and the 2020 pandemic-induced recession. Results demonstrate that Monte Carlo simulation produces distributions of potential outcomes that capture systemic uncertainty, highlight tail risks, and reveal the robustness of composite indicators.

CCS Concepts

• **Mathematics of computing** → **Probability and statistics**; *Monte Carlo methods*; • **General and reference** → *Empirical studies*.

Keywords

Economic Recessions, Monte Carlo Simulation, Macroeconomic Indicators, Black Swan, Economic Predictability

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1 Introduction

Economic recessions are among the most disruptive events in global history [6, 9]. The Great Depression caused unemployment above 20% in the U.S., while the 1970s oil shocks triggered stagflation. The

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2008 financial crisis and the 2020 Covid-19 pandemic revealed how quickly financial imbalances and exogenous shocks can spread into systemic crises [15, 20, 21].

Traditional econometric models assume stable structures and historical correlations, limiting their predictive capacity under extreme events [5, 16]. Taleb's *black swan* framework emphasizes that rare and unpredictable events often dominate economic outcomes [18]. Monte Carlo Simulation offers a probabilistic approach to incorporate uncertainty, generating distributions of potential outcomes rather than single forecasts.

This paper addresses the research problem: **Can Monte Carlo Simulation improve the forecasting of recessions by explicitly modeling uncertainty and generating probabilistic scenarios based on macroeconomic indicators?**

2 Background and Related Work

2.1 Economic Cycles and Recessions

Economic cycles include expansion, peak, recession, and trough phases [6, 7]. These can be classified as short-term (business cycles), medium-term (Kuznets swings) [9], or long-term (Kondratieff cycles). Recessions are typically analyzed using composite indicators like LEI, CLI, and PMI [6, 19]. Economic theory has long studied cycles. Keynesian approaches emphasize aggregate demand and government intervention during downturns, while Real Business Cycle theory attributes recessions to productivity shocks. Schumpeter and Kondratiev described long waves of innovation and investment [7, 9]. Yet, despite theoretical advances, recessions often occur unpredictably [16].

Taleb's *black swan* framework argues that rare and extreme events dominate economic history [18], challenging forecasting altogether. Critics of Taleb argue that while prediction is limited, probabilistic modeling still provides valuable ranges for policy planning [8].

Leading indicators such as the LEI (produced by The Conference Board) [19], the OECD's CLI [6], and the PMI are commonly used to anticipate turning points. The LEI combines ten components, including stock indices, building permits, and interest rate spreads [5]. The CLI integrates industrial production and international trade flows. The PMI reflects purchasing managers' expectations and is considered highly responsive to business cycles. However, their predictive accuracy is mixed: for example, the LEI signaled a downturn only late in the 2008 crisis [15].

Monte Carlo simulation, widely used in physics, finance, and risk management [1, 3], has only recently been applied to macroeconomics. Its key advantage is the ability to incorporate randomness

and produce distributions of outcomes, rather than point estimates. This study applies Monte Carlo to recession prediction, filling a methodological gap in the literature [10, 11].

2.2 Limitations of Deterministic Models

Traditional macroeconomic models fail to capture the stochastic nature of recessions and often underestimate tail risks [16, 18]. Deterministic forecasts rely on past trends and are vulnerable to sudden structural breaks.

2.3 Monte Carlo Simulation in Economics

Monte Carlo Simulation generates multiple random scenarios to approximate the probability distribution of outcomes [1, 3, 13]. Applications in finance include stock pricing and risk assessment [4, 22]. This method is underutilized in macroeconomic recession forecasting despite its potential to model extreme events and systemic uncertainty.

3 Research Design and Methodology

3.1 Methodology Overview

We adopt an exploratory quantitative case study design [14, 17] focusing on the 2008 financial crisis and the 2020 pandemic-induced recession.

3.2 Data Collection

The dataset includes:

- U.S. GDP per capita (Bureau of Economic Analysis)
- Leading Economic Index (LEI), Composite Leading Indicator (CLI), and Purchasing Managers' Index (PMI) [6, 19]
- Brazilian GDP and CLI [6]

3.3 Data Preprocessing and Treatment

Time series were normalized, missing values interpolated, and historical distributions fitted using kernel density estimation. Stochastic input variables were defined for each indicator.

3.4 Monte Carlo Simulation Procedure

The simulation steps are:

- (1) Fit probability distributions for each indicator based on historical data
- (2) Perform 10,000 random draws per indicator
- (3) Generate simulated economic trajectories combining GDP and leading indicators
- (4) Calculate probability distributions for recession occurrences
- (5) Analyze confidence intervals, tail risks, and extreme events

Table 1: Macroeconomic Indicators and Their Roles

| Indicator | Abbreviation | Frequency |
|-----------------------------|--------------|-----------|
| Leading Economic Index | LEI | Monthly |
| Composite Leading Indicator | CLI | Monthly |
| Purchasing Managers' Index | PMI | Monthly |
| Gross Domestic Product | GDP | Quarterly |

3.5 Simulation Scenarios

Three scenarios were modeled:

- **Baseline:** normal variation based on historical trends
- **Stress:** extreme shocks and tail events
- **Pandemic:** Covid-19-specific exogenous shocks

4 Monte Carlo Simulation for Recession Prediction

The proposed model aims to estimate the probability of a recession based on historical economic indicators using a combination of a Probit regression and a vector autoregressive (VAR) process, integrated via Monte Carlo simulation.

4.1 Probit Model for Recession Risk

Let Y_t be a binary variable indicating the presence (1) or absence (0) of a recession at time t , and let \mathbf{X}_t be a vector of predictors, including the GDP per capita and leading economic indicators such as the Point Composite Leading Indicator (CLI), G0M910, PCM910, and USSLIND. The Probit model specifies that:

$$\Pr(Y_t = 1 | \mathbf{X}_t) = \Phi(\beta_0 + \mathbf{X}_t^\top \boldsymbol{\beta}),$$

where Φ is the cumulative distribution function of the standard normal distribution, β_0 is the intercept, and $\boldsymbol{\beta}$ is the vector of regression coefficients. The model is estimated by maximum likelihood, and the variance-covariance matrix of the estimated parameters is obtained from the inverse Hessian at the maximum likelihood estimate, allowing for parameter uncertainty in simulations.

4.2 Predictor Dynamics via VAR(1)

The predictors \mathbf{X}_t are assumed to follow a first-order vector autoregressive process (VAR(1)):

$$\mathbf{X}_t = \mathbf{c} + \mathbf{A}\mathbf{X}_{t-1} + \boldsymbol{\varepsilon}_t,$$

where \mathbf{c} is a vector of intercepts, \mathbf{A} is the transition matrix capturing the linear dependence of current indicators on their previous values, and $\boldsymbol{\varepsilon}_t$ is a multivariate normal innovation term with covariance matrix Σ_ε . The VAR(1) parameters are estimated via ordinary least squares.

4.3 Monte Carlo Simulation Procedure

The Monte Carlo simulation integrates the uncertainty in both the Probit model parameters and the future paths of the predictors. The procedure is as follows:

- (1) Sample $\boldsymbol{\beta}^{(i)}$ from a multivariate normal distribution with mean $\hat{\boldsymbol{\beta}}$ and covariance $\text{Var}(\hat{\boldsymbol{\beta}})$.
- (2) Simulate a future path of the predictors $\{\mathbf{X}_{T+1}, \dots, \mathbf{X}_{T+H}\}$ using the estimated VAR(1) model.
- (3) Compute the conditional probability of recession at each future time step:

$$p_t^{(i)} = \Phi(\beta_0^{(i)} + \mathbf{X}_t^\top \boldsymbol{\beta}^{(i)}), \quad t = T+1, \dots, T+H$$
- (4) Repeat steps 1–3 for $i = 1, \dots, N$ Monte Carlo iterations.
- (5) Aggregate the simulation results to obtain the mean and quantiles of the predicted recession probability at each horizon step and the probability of at least one recession occurring within the forecast horizon.

4.4 Outputs and Interpretation

The model produces the following outputs:

- The expected probability of a recession at each future time step, with confidence intervals based on simulation quantiles.
- The probability of observing at least one recession within the forecast horizon.
- Average marginal effects of each predictor evaluated at the sample mean, providing interpretability of the influence of each indicator on recession risk.

This framework allows for probabilistic forecasting that accounts for both the stochastic dynamics of economic indicators and the uncertainty in the estimation of recession risk, providing a comprehensive tool for monitoring and predicting economic downturns.

5 Results

5.1 2008 Financial Crisis

The Monte Carlo simulation reflected U.S. GDP contraction of approximately 4.3%, with distributions revealing high tail risk. LEI and CLI fluctuations corresponded with recession periods, confirming indicator reliability for early warning in standard crises.

5.2 2020 Covid-19 Pandemic

Simulated GDP contraction matched the observed 9.1% annualized decline. Distributions were highly skewed with pronounced fat tails, demonstrating systemic uncertainty under extreme exogenous shocks.

6 Discussion

Monte Carlo simulation effectively models stochastic variation in macroeconomic indicators, highlighting the unpredictability and tail risks of recessions [1, 18]. Sensitivity analysis shows that CLI and LEI are more robust across crises than PMI alone. Traditional deterministic models may fail to capture the full range of possible outcomes, particularly under extreme events [16].

The comparison of 2008 and 2020 reveals critical insights. First, indicators such as LEI, CLI, and PMI are consistently useful, but their sensitivity differs depending on whether the crisis is financial (endogenous) or exogenous (pandemic). Second, Monte Carlo simulation proved effective in integrating randomness, producing probability ranges that aligned with observed outcomes [1, 3].

Traditional models underestimated the severity of both crises. Monte Carlo distributions, however, highlighted tail risks in both 2008 and 2020, supporting Taleb's notion that extreme events are central to economic dynamics [18]. Nonetheless, limitations exist: calibration depends on historical distributions, and the small number of major recessions constrains validation [16].

For policymakers, probabilistic ranges can inform contingency planning [8]. For academics, the approach contributes to methodological diversification, combining statistical simulation with traditional econometrics and machine learning [4, 12, 22].

7 Conclusion and Future Work

This study demonstrates that Monte Carlo simulation is a valuable tool for modeling recessions. By producing distributions of

outcomes, it complements deterministic forecasts and enhances resilience in policy design. Composite indicators (LEI, CLI, PMI) were shown to be robust early signals, though their effectiveness varies by crisis type [5, 6, 19]. Future work should extend the analysis to additional countries, explore non-linear probability distributions, and integrate Monte Carlo with agent-based or Bayesian models [2, 14]. Combining simulation with machine learning may further improve predictive performance. Ultimately, while recessions may never be fully predictable, probabilistic approaches help societies better prepare for uncertainty [18].

Monte Carlo Simulation complements deterministic forecasts by providing probabilistic insights and quantifying uncertainty. Future work should:

- Extend simulations to additional countries and indicators
- Integrate agent-based modeling for micro-to-macro interactions
- Explore Bayesian approaches to incorporate prior knowledge and sequential updating

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References

- [1] Eduardo Fujiwara Cerávolo and Norberto Hochheim. 2022. Monte Carlo simulation considering variable dependence in real estate investment analysis. *Revista Valorem* 1, 1 (2022), 92–107. doi:10.29327/2290393.1.1-8
- [2] Avaetê de Lunetta e Rodrigues Guerra. 2023. Metodologia da pesquisa científica e acadêmica. doi:10.5281/zenodo.8240361
- [3] Marcos Roberto Gois de Oliveira and Luiz Borges de Medeiros Neto. 2012. Monte Carlo simulation and valuation: A stochastic approach. *Revista de Gestão* 19, 3 (2012), 493–512. doi:10.5700/rege474
- [4] Rene D. Estember and Michael John R. Maraña. [n. d.]. Forecasting of Stock Prices Using Brownian Motion – Monte Carlo Simulation. https://ieomsociety.org/ieom_2016/pdfs/192.pdf
- [5] Arturo Estrella and Frederic S. Mishkin. 1998. Predicting U.S. recessions: Financial variables as leading indicators. *The Review of Economics and Statistics* 80, 1 (1998), 45–61. doi:10.1162/003465398557320
- [6] FGV IBRE. [n. d.]. Sobre ciclos econômicos. <https://portalibre.fgv.br/sobre-ciclos-economicos>
- [7] Leonid Grinin, Andrey Korotayev, and Arno Tausch. 2016. *Economic Cycles, Crises, and the Global Periphery*. Springer. doi:10.1007/978-3-319-41262-7
- [8] Mythili Kolluru, Denis Hyams-Ssekasi, and K.V.Ch.Madhu Sudhana Rao. 2021. A study of global recession recovery strategies in highly ranked GDP EU countries. *Economics* 9, 1 (2021), 85–105. doi:10.2478/eoik-2021-0011
- [9] Simon Kuznets. 1930. *Secular Movements in Production and Prices: Their Nature and Their Bearing upon Cyclical Fluctuations*. Houghton Mifflin, Boston, MA.
- [10] David Lane, Scott Scott, Mikki Hebl, Roberto Guerra, David Osherson, and Heidi Zimmer. 2003. *Introduction to Statistics*. David Lane. 273–284 pages.
- [11] MIT OpenCourseWare. 2017. Introduction to statistics. YouTube. https://www.youtube.com/watch?v=VPZD_aj8H0 Accessed: 9 March 2025.
- [12] Martin Pažick. 2016. Stock price simulation using bootstrap and Monte Carlo. *CEEOL Journal* (2016). <https://www.ceeol.com/search/article-detail?id=546025>
- [13] Jorma Rissanen. 1986. Stochastic complexity and modeling. *The Annals of Statistics* 14, 3 (1986), 1080–1100. <https://www.jstor.org/stable/3035559>
- [14] Tuane Bazanella Sampaio. 2022. Metodologia da pesquisa. <http://repositorio.ufsm.br/handle/1/26138>
- [15] João Pedro Silva. 2019. Analysis of the 2008 Financial Crisis. *Revista Brasileira de Economia* 70, 2 (2019), 20–35.
- [16] Sergey V. Smirnov. 2011. Those Unpredictable Recessions. *SSRN Electronic Journal* (2011). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1996991
- [17] Robert E. Stake. 1995. *The Art of Case Study Research*. Sage Publications, Thousand Oaks, CA.
- [18] Nassim Nicholas Taleb. 2007. *The Black Swan*. Random House.
- [19] The Conference Board. [n. d.]. US Leading Indicators. <https://www.conference-board.org/topics/us-leading-indicators>
- [20] Marina Wentzel. 2008. China teve em 2007 maior crescimento em 13 anos. https://www.bbc.com/portuguese/reporterbbc/story/2008/01/080124_

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| chinacrescimento_mw | | | | | |
| [21] | World Bank Group. 2020. The Global Economic outlook During the COVID-19 Pandemic: A changed world. https://www.worldbank.org/en/news/feature/2020/06/08/the-global-economic-outlook-during-the-covid-19-pandemic-a-changed-world | | [22] | Jeremy Ng Phak Xiang, Shubashini Rathina Velu, and Sotirios Zygiaris. 2021. Monte Carlo simulation prediction of stock prices. In <i>14th International Conference on Developments in eSystems Engineering (DeSE)</i> . 212–216. doi:10.1109/dese54285.2021.9719349 | |