UNIVERSIDAD AUTÓNOMA DE NUEVO LEÓN
FACULTAD DE ECONOMÍA
DIVISION DE ESTUDIOS DE POSGRADO

“ESSAYS ON DYNAMIC MACROECONOMICS AND MACHINE LEARNING IN THE ECONOMIC CONTEXT OF MEXICO”

Por

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Tesis presentada como requisito parcial para obtener el grado de Doctorado en Ciencias Económicas

SEPTIEMBRE 2024

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Introduction

With its abundant natural resources, strategic geographical location—acting as a North American trade hub with access to the Atlantic and Pacific oceans—and a youthful population, Mexico has considerable potential to emerge as a significant player on the global economic stage. However, realizing this potential necessitates overcoming substantial challenges, particularly in managing the impacts of macroeconomic shocks and crises. These challenges are critical to address because they directly influence the country's stability and growth prospects. Persistent increases in public debt over several decades have limited Mexico's capacity to effectively manage crises, as demonstrated by its comparatively restrained response to the recent health emergency. Furthermore, while providing vital employment opportunities, the substantial informal sector impedes economic planning and heightens vulnerabilities during economic downturns due to its lack of transparency. Additionally, delays in institutions publishing critical economic indicators hinder timely economic analysis and exacerbate uncertainty during periods of recession.

In the first chapter, we examine the impact of fiscal policy in Mexico during recessions, focusing on public spending instruments such as government consumption, public investment, and income transfers. Our analysis aims to design a fiscal policy that mitigates the impact of recessions and serves as a fiscal consolidation strategy, thereby avoiding the adverse effects of increasing public debt.

For this purpose, we first estimate a DSGE model for Mexico to assess the multiplier effect of public spending instruments. We found that government consumption is the spending instrument that most impacts economic activity, while transfers even have long-term negative consequences. Subsequently, fiscal policy is designed based on an increase in the spending component that generates the greatest impact on economic activity, financed by cuts in that component with the least impact, i.e., government consumption increases funded by reductions in government income transfers.

Our results indicate that the fiscal policy design proposed in this chapter is effective in mitigating the impact of a recession and, at the same time, acting as a fiscal consolidation policy. Furthermore, this fiscal policy's effect on economic activity cushions the recession's impact and makes it less persistent compared to countercyclical fiscal policies financed by increases in public debt.

The second chapter analyzes the formal sector's impact on the main economic aggregates: economic growth, employment, and inflation during the COVID-19 crisis. The COVID-19 pandemic significantly impacted the global economy, with variable effects on economic growth, employment, and inflation rates in different countries and regions.

Latin America and the Caribbean (LAC) region experienced the most severe consequences for economic growth and employment, while the change in inflation was relatively less affected. A notable characteristic of the LAC region is its high level of informality and its close relationship with inflation dynamics.

A NK-DSGE model calibrated for Mexico as a representative informal economy in this region was built and simulated to understand the role of informality in the COVID-19 crisis. The findings highlight that the informal sector exacerbates the crisis's negative impacts on economic growth and employment rates but mitigates the inflationary effects of the containment measures. In summary, the high rates of informality in the LAC region play an important role in shaping the consequences of restrictive measures to curb the pandemic on the economy.

The third chapter contributes to the forecasting literature in Mexico by using machine learning models fed with big data to nowcast economic indicators and monitor economic activity promptly, given the delay in the publication of official economic indicators.

We develop a Nowcasting exercise for the Monthly Economic Activity Indicator (IMAI in Spanish). This indicator is strongly related to the Global Indicator of Economic Activity (IGAE in Spanish), which is strongly correlated with GDP. However, the IMAI offers an advantage over the IGAE since its publication is only presented one month late, while the latter indicator is around two months late.

First, we choose among a large set of covariates used to forecast indicators, such as the IGAE and the GDP, with the condition that they are more timely than the IMAI, such as economic, financial, and survey-based indicators. Furthermore, we added a large set of non-traditional indicators based on the Big category Data based on internet searches through the Google search engine. Then, we use variable selection methods (LASSO, Adaptive LASSO, Elastic Net, and Adaptive Elastic Net) to filter out those indicators that do not contribute to the nowcasting exercise and avoid the problem of overfitting in the model. We employed dynamic factor models (DFM) alongside variable selection models, widely used in the forecasting literature.

We compared these models using mean absolute error (MAE) as the primary metric to evaluate their performance in IMAI nowcasting. Notably, our analysis reveals the increasing relevance of non-traditional indicators, particularly during recessionary periods, and showcases the superior performance of LASSO and Elastic Net models over dynamic factor models. The selection between these models poses a significant dilemma, with Elastic Net offering greater flexibility at the cost of computational complexity, while LASSO favors computational efficiency and parsimonious variable selection.

This dissertation comprises the chapters mentioned above. Each chapter provides detailed discussions of related literature, methodology, results, conclusions, limitations, public policy implications, and potential future extensions.

Chapter 1

Mitigating Recessions with Fiscal Consolidation: A Multiplier-Based Approach for Highly Indebted Countries

1.1 Introduction

Public institutions such as the central bank and government play an important role in regulating economic fluctuations. They achieve this by manipulating key instruments such as government spending, taxes, and interest rates. For instance, during recessions, advanced economies often witness central banks lowering interest rates while governments increase spending, as documented by Vegh & Vuletin (2015).

Central banks enjoy greater flexibility in adjusting interest rates compared to the limitations faced by governments when increasing spending. Unlike monetary policy, fiscal policy faces limitations due to budgetary constraints and borrowing capacity. For instance, a government with high public debt has less room for countercyclical spending increases Burriel et al. (2020). Conversely, governments committed to fiscal consolidation may not raise spending for extended periods Ormaechea & Morozumi (2013). This creates a challenge: governments with public finances might struggle to implement countercyclical spending policies during recessions. Consequently, these recessions could be deeper or longer-lasting in such cases, as the multiplier effect of government expenditure is absent.

Mexico has consistently struggled with fiscal deficits, which austerity programs have not alleviated due to various external shocks impacting the nation's public finances Moreno-Brid et al. (2017). During the 2008 financial crisis, the government implemented a countercyclical fiscal policy, increasing public investment through debt financing. This situation worsened with the sharp decline in oil prices in 2012, leading to the 2014 tax reform. Additionally, the recent COVID-19 crisis has heightened concerns about the sustainability of Mexico's public debt, as noted by Rivas Valdivia (2021).

Despite efforts to reduce the debt-to-GDP ratio, these past events have hindered progress. As a result, Mexico's gross debt-to-GDP ratio increased from 21% in 2000 to 47.5% in 2023, according to the Ministry of Finance and Public Credit. This financial strain has limited the government's ability to respond to subsequent economic crises. Even Hannan et al. (2022)

observed that Mexico's fiscal response to the COVID-19 crisis was moderate compared to its peers, reflecting a reluctance to issue new debt. Therefore, it is of utmost importance to design a fiscal policy capable of regulating economic activity that is not costly for the country's public finances.

The spending multiplier theory has been growing. Recent works analyze the disaggregation of public spending and its multipliers instead of taking government spending multiplier as a whole (see, for example, Corsetti et al. (2012); Ormaechea & Morozumi (2013); Cortuk & Guler (2015); Varthalitis (2019), among others). In these studies, it has been found that the multiplier effect of each government expenditure component is of different size and impacts macroeconomic aggregates differently; this makes it possible to drive fiscal policy efficiently or to serve specific objectives. Furthermore, the size of multipliers depends on different characteristics of the economy (openness degree, exchange regime, public indebtedness, among others). Still, the spending instruments with the greatest multiplier are those that make up government consumption, such as the public sector wage bill and the purchase of private goods and services, and those that generate the least multiplier effect are transfers.

Moreover, the disaggregation of public spending has been examined to analyze fiscal consolidation policies. For instance, Forni et al. (2010) suggests that decreasing government consumption (including the purchase of goods, services, and public salaries) can reduce debt and improve welfare by allowing for lower taxes. In contrast, Stähler & Thomas (2012) investigates the effects of fiscal consolidation policies by reducing different components of public spending. Their findings indicate that fiscal consolidation is less detrimental when reducing the public sector wage bill than cutting public investment. While Philippopoulos et al. (2016) suggests reducing government consumption and capital taxes to generate the least possible economic damage.

From the above, it is clear that high debt during a crisis is highly unfavorable. Addressing the crisis could involve stimulating the fiscal instrument with the highest multiplier: government consumption. At the same time, reducing this component appears to be the best alternative for achieving fiscal consolidation. This theoretical framework gives rise to executing a fiscal policy that consists of a redistribution of the budget earmarked for public spending to deal with a recession and overindebtedness, i.e., cutting the funding to the components with the lowest fiscal multiplier and using this amount to finance those with the highest multiplier. In this way, we seek a positive effect on GDP without increasing government spending, giving room to reduce the debt-to-GDP ratio.

We estimate an NK-DSGE model for the Mexican economy to carry out this exercise. Within the model, we use a disaggregated approach to public spending, which consists of three instruments: government consumption, public investment, and transfers. We keep the tax rates constant following the tax-smoothing theory. Once the model is estimated, we simulate a recession caused by an aggregate demand shock, similar to Aursland et al. (2020). Then, we compare the effect of this crisis when there is and when there is no government intervention. Government intervention is done through two policies. The first addresses the crisis generated by increasing spending on the component with the highest multiplier financed with public debt. The second policy consists of increasing spending on the above component, funded by cuts to the element with the lowest multiplier.

Once we do this exercise, we observe how output and debt react through the three scenarios above. First, we found that the component with the highest multiplier is government consumption, while the item with the lowest multiplier is government income transfers. Second, we note that a cut-financed fiscal policy manages to mitigate the impact of the crisis as well as debt-financed fiscal policy; however, it is more effective in reducing debt-GDP, although this leads to social costs due to decreased transfers.

The rest of the paper is organized as follows: Section 1.2 details the NK-DSGE model used to evaluate the impact of fiscal policy in Mexico. The estimation results are presented in Section 1.3. The main results are discussed in Section 1.4. Finally, section 1.5 concludes.

1.2 Model

The model represents a closed economy populated by three agents that live in infinite periods: households, firms, and a government. A fraction of the population $\omega \in (0,1)$ is looking-forward optimizers who hold government bonds, invest in private capital, rent capital, and receive profits from firms, which we will call "savers". In contrast, the remaining fraction $1-\omega \in (0,1)$ are the rule of thumb households, consuming all their disposable income, which we will call "non-Savers".

On the production side, there are two sectors: the final and intermediate goods. In the final good sector, there is a single representative firm that is a price taker and uses the basket of intermediate goods to produce the final good of the economy. In the intermediate goods sector, a large number of firms operate in monopolistic competition, which uses public capital, private capital, and household labor to produce a differentiated intermediate good.

The government oversees fiscal and monetary policy. Fiscal policy consists of collecting income through taxes on households and issuing public debt to finance different activities. Monetary policy involves adjusting the nominal interest rate following a standard Taylor rule.

The following subsections detail the problems the two types of households faced, the decisions made in the two productive sectors, and the fiscal and monetary policy operations.

1.2.1 Households

The instantaneous utility of the representative saver household depends on its effective consumption $\widetilde{C}_{s,t}$ and negatively on the labor supply $L_{s,t}$. The present value of the expected utility throughout the life of each household is given by:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \xi_t \log\left(\widetilde{C}_{s,t} - \chi_t \frac{L_{s,t}^{1+\varphi}}{1+\varphi}\right) \tag{1.1}$$

where $\mathbb{E}_0$ represents the mathematical operator of expectations conditioned on the information available in the initial period. The parameter $\beta \in (0,1)$ is the subjective discount factor, $\varphi \in (0,\infty)$ denotes the inverse of the Frisch labor supply elasticity. ξ_t and χ_t are preference and labor supply shocks of the saver household, respectively, which follow log AR(1) stationary processes given by:

$$\frac{\xi_t}{\xi_{ss}} = \left(\frac{\xi_{t-1}}{\xi_{ss}}\right)^{\rho_\xi} \exp\left(\sigma_\xi \varepsilon_{\xi,t}\right) \tag{1.2}$$

$$\frac{\chi_t}{\chi_{ss}} = \left(\frac{\chi_{t-1}}{\chi_{ss}}\right)^{\rho_\chi} \exp\left(\sigma_\chi \varepsilon_{\chi,t}\right) \tag{1.3}$$

where $\varepsilon_{\xi,t}, \varepsilon_{\chi,t} \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$, represent the disturbances in preferences and labor supply, respectively. ρ_ξ, $\rho_\chi \in (0,1)$ capture the persistence of the respective shocks and $\sigma_\xi, \sigma_\chi \in (0,\infty)$ its corresponding standard deviations.

The effective consumption of the saver household is composed of its private consumption $C_{s,t}$ and government consumption $G_{C,t}$, where Bouakez & Rebei (2007) suggests modeling with an elasticity of substitution function constant (CES) which we presented as follows:

$$\widetilde{C}_{s,t} \equiv \left[\phi C_{s,t}^{\frac{\nu-1}{\nu}} + (1-\phi) G_{C,t}^{\frac{\nu-1}{\nu}}\right]^{\frac{\nu}{\nu-1}}, \tag{1.4}$$

the parameter $\phi \in [0,1]$ is the weight of private consumption on effective consumption, and $\nu \in (0,\infty)$ measures the elasticity of substitution between public and private consumption. When $0 < \nu < 1$, private and public consumption are complementary; when $\nu = 1$, the effective consumption function becomes separable in time; if $\nu > 1$, they are substitutes, and if $\nu \to \infty$ private and government consumption are perfect substitutes.

The budget constraint of the representative saver household in real terms is given by:

$$(1+\tau_C)C_{s,t} + I_{s,t} + B_{s,t} \leq (1-\tau_L)W_t L_{s,t} + (1-\tau_K)Q_t K_{s,t} + \Psi_{s,t} + G_{T,t} + \frac{R_{t-1}}{\Pi_t} B_{s,t-1}, \tag{1.5}$$

where $I_{s,t}$ and $B_{s,t}$ represent the saver household's private capital investment and purchases of government bonds, respectively. The real wage rate and capital income are represented by W_t and Q_t, respectively. $\Psi_{s,t}$ denotes the profits transferred from the firms that they own, $G_{T,t}$ represent the common transfers that households receive from the government, R_t is the gross nominal interest rate and Π_t denotes the gross inflation rate. The parameters τ_C, τ_L, and $\tau_K \in (0,1)$ represent the consumption, payroll, and capital tax rates, respectively.

The representative saver household invests in private capital to compensate the capital stock depreciated at a rate $\delta \in (0,1)$ or to accumulate a greater stock that generates greater rental income, so the capital of the saver household builds up according to the following capital's law of motion:

$$K_{s,t+1} = (1-\delta) K_{s,t} + I_{s,t} - \frac{\vartheta}{2}\left(\frac{I_{s,t}}{I_{s,t-1}} - 1\right) I_{s,t}, \tag{1.6}$$

here, $\delta \in (0,1)$ measures the depreciation rate of private capital and $\vartheta \in (0,\infty)$ denotes the investment adjustment costs. Therefore, the problem of saver households is to maximize their expected utility throughout their life by choosing their consumption, hours of work, private capital of the next period, private investment, and purchase of government bonds.

The rule-of-thumb household has the same preferences as the optimizer. It chooses only consumption and labor, and its budget constraint is simply this:

$$(1+\tau_C)C_{n,t} = (1-\tau_L)W_t L_{n,t} + G_{T,t}, \tag{1.7}$$

Therefore, the first-order conditions with respect to private consumption and labor supply are the same between household groups, which implies that $L_{s,t} = L_{n,t}$.

The aggregates of consumption, employment, government bond holdings, private investment, private capital, and profits from firms are given by:

$$C_t = \omega C_{s,t} + (1-\omega)C_{n,t}, \tag{1.8}$$

$$L_t = \omega L_{s,t} + (1-\omega) L_{n,t}, \tag{1.9}$$

$$B_t = \omega B_{s,t} \tag{1.10}$$

$$I_t = \omega I_{s,t}, \tag{1.11}$$

$$K_t = \omega K_{s,t}, \tag{1.12}$$

$$\Psi_t = \omega \Psi_{s,t}. \tag{1.13}$$

1.2.2 Firms

Production is divided into two sectors. In the first sector, a continuum of firms, indexed by $j \in [0, 1]$, produces differentiated intermediate goods used as inputs in the second sector to create a final good.

A single price-taker firm produces the final good and operates through CES technology that uses as inputs the goods produced in the intermediate goods sector so that:

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.14}$$

where the parameter $\epsilon \in (1, \infty)$ measures the elasticity of substitution between the different varieties $Y_t(j)$. The cost minimization problem for the firm producing the final good leads to the following demand for each intermediate good j given by:

$$Y_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{\epsilon} Y_t, \tag{1.15}$$

where P_t represents the price of the final good and $P_t(j)$ the price of the intermediate good j. Finally, the zero profit condition implies that the price index is:

$$P_t = \left(\int_0^1 P_t(j)^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}. \tag{1.16}$$

In the intermediate goods sector, competitive monopolistic firms face a Cobb-Douglas production technology that uses private capital, public capital, and household labor, given by:

$$Y_t(j) = A_t G_{K,t}^{\gamma} K_t(j)^{\alpha} L_t(j)^{1-\alpha} - \Phi, \tag{1.17}$$

here, A_t represents the level of productivity common among the intermediate goods sector, and $G_{K,t}$ denotes the public capital stock. $\alpha \in [0, 1]$ is a structural parameter related to the share of capital income in the intermediate goods sector, $\gamma \in [0, \infty)$ denotes the elasticity of public capital on the production of intermediate goods and $\Phi \in [0, \infty)$ represents the common fixed costs. Productivity follows a log AR(1) stationary process given by:

$$\frac{A_t}{A_{ss}} = \left(\frac{A_{t-1}}{A_{ss}}\right)^{\rho_A} \exp(\sigma_A \varepsilon_{A,t}), \tag{1.18}$$

where $\varepsilon_{A,t} \overset{i.i.d.}{\sim} \mathcal{N}(0, 1)$ represents productivity shocks, $\rho_A \in (0, 1)$ and σ_A captures the persistence and standard deviations of productivity shocks, respectively.

Each firm of intermediate goods j faces costs for adjusting its price à la Rotemberg (1982), which are assumed to be quadratic and zero in the steady state. Therefore, firm j sets its price $P_t(j)$ to maximize its profits given by

$$\max_{P_{t+k}(j)} \mathbb{E}_t \sum_{k=0}^{\infty} \Lambda_{t,t+k} \left[\left(\frac{P_{t+k}(j)}{P_{t+k}} - \frac{MC_{t+k}}{P_{t+k}} \right) Y_{t+k}(j) - \frac{\theta}{2} \left(\frac{P_{t+k}(j)}{P_{t+k-1}(j)} - 1 \right)^2 Y_{t+k} \right], \tag{1.19}$$

where Λ_t is the stochastic household discount factor, MC_t denotes the common marginal cost within the sector, and $\theta \in (0, \infty)$ represents the cost associated with price adjustment, which determines the degree of nominal rigidity in prices.

1.2.3 Government

The monetary policy follows a standard Taylor-type feedback rule in which the nominal interest rate responds to its lagged value, inflation, and the output gap, given by:

$$\frac{R_t}{R_{ss}} = \left(\frac{R_{t-1}}{R_{ss}}\right)^{\rho_R} \left[\left(\frac{\Pi_t}{\Pi_{ss}}\right)^{\psi_{R,\Pi}} \left(\frac{Y_t}{Y_{ss}}\right)^{\psi_{R,Y}}\right]^{(1-\rho_R)} \exp\left(\sigma_R \varepsilon_{R,t}\right) \tag{1.20}$$

here $\rho_R \in (0,1)$ measures the softening of monetary policy on the nominal interest rate, while $\psi_{R,\Pi} \in (1,\infty)$ and $\psi_{R,Y} \in [0,\infty)$ captures the nominal interest rate reaction to the steady-state deviations of inflation and output. $\varepsilon_{R,t} \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$ represents a monetary policy shock and $\sigma_R \in (0,\infty)$ its standard deviation.

On the side of fiscal policy, the government finances public spending on government consumption, public investment, and transfers by raising income through household taxation or the issuance of debt; therefore, we can express the government budget constraint as:

$$\underbrace{G_{C,t} + G_{I,t} + G_{T,t}}_{\text{Government spending}} + \frac{R_{t-1}}{\Pi_t} D_{t-1} \leq \underbrace{\tau_C C_t + \tau_L W_t L_t + \tau_K Q_t K_t}_{\text{Tax revenue}} + D_t, \tag{1.21}$$

here $G_{I,t}$ denotes public investment. The public investment expenditure creates new public capital stock as follows:

$$G_{K,t+1} = (1-\delta_G) G_{K,t} + G_{I,t} \tag{1.22}$$

where $\delta_G \in (0,1)$ represents the depreciation rate of public capital. Following Drygalla et al. (2020), we assume that government spending is carried through the following fiscal policy rules:

$$\frac{G_{C,t}}{G_{C,ss}} = \left(\frac{G_{C,t-1}}{G_{C,ss}}\right)^{\rho_C} \left[\left(\frac{D_{t-1}}{D_{ss}}\right)^{\psi_{C,D}} \left(\frac{Y_t}{Y_{ss}}\right)^{\psi_{C,Y}}\right]^{(1-\rho_C)} \exp(\varepsilon_{C,t}) \tag{1.23}$$

$$\frac{G_{I,t}}{G_{I,ss}} = \left(\frac{G_{I,t-1}}{G_{I,ss}}\right)^{\rho_I} \left[\left(\frac{D_{t-1}}{D_{ss}}\right)^{\psi_{I,D}} \left(\frac{Y_t}{Y_{ss}}\right)^{\psi_{I,Y}}\right]^{(1-\rho_I)} \exp(\varepsilon_{I,t}) \tag{1.24}$$

$$\frac{G_{T,t}}{G_{T,ss}} = \left(\frac{G_{T,t-1}}{G_{T,ss}}\right)^{\rho_T} \left[\left(\frac{D_{t-1}}{D_{ss}}\right)^{\psi_{T,D}} \left(\frac{Y_t}{Y_{ss}}\right)^{\psi_{T,Y}}\right]^{(1-\rho_T)} \exp(\varepsilon_{T,t}) \tag{1.25}$$

where $\varepsilon_{C,t}, \varepsilon_{I,t}, \varepsilon_{T,t} \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$ represent the shocks in government consumption, public investment, and transfers, respectively, $\rho_C, \rho_I, \rho_T \in (0,1)$ the persistence of the respective shocks and $\sigma_C, \sigma_I, \sigma_T$, its standard deviation. The parameters $\psi_{C,D}, \psi_{I,D}, \psi_{T,D} \in (-\infty, \infty)$ capture the reaction of government spending components to issued public debt and $\psi_{C,Y}, \psi_{I,Y}, \psi_{T,Y} \in (-\infty, \infty)$ capture the reaction of government spending components to output.

1.2.4 Market Clearing Conditions

The public debt is equal to government bond holdings by saver households, therefore:

$$D_t = B_t = \omega B_{s,t}. \tag{1.26}$$

The aggregate profits of monopolistic competitive firms producing intermediate goods that saver households own, given the symmetry property, are given by:

$$\Psi_t = \omega \Psi_{s,t} = Y_t - W_t L_t - Q_t K_t - \frac{\theta}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t. \tag{1.27}$$

Last, the final good produced in the economy is intended for private consumption, private investment, government consumption, and public investment, as well as to cover price adjustment costs. Therefore, it is required that:

$$Y_t = C_t + I_t + G_{C,t} + G_{I,t} + \frac{\theta}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t. \tag{1.28}$$

1.3 Estimation

The model is estimated using Bayesian techniques and quarterly data from Mexico to cover 2005/Q1 - 2024/Q1, which we will detail later. Some parameters are obtained from the literature or calibrated to match some ratios that characterize the Mexican economy, while we get the rest through Bayesian estimation. Below, we detail the calibration and parameter estimation process.

1.3.1 Calibrated Parameters

We detail the standard parameters from the Real Business Cycles (RBC) modeling literature. We set the parameter that measures the elasticity of private capital in the firm's production function to a standard value of $\alpha = 0.333$. The discount factor is set to $\beta = 0.990$ so that the steady-state value of the real interest rate is 4% per year. We set the inverse of Frisch labor supply elasticity to $\varphi = 1.000$. The private capital depreciation rate is set at its standard value of $\delta = 0.025$, implying an annual private capital depreciation rate of 10%. We take the weight of private consumption in the effective consumption from Bouakez & Rebei (2007); this value is $\phi = 0.800$.

Now, we describe the standard parameters obtained from the New-Keynesian (NK) literature. We set the elasticity of substitution between varieties at $\epsilon = 6.000$, implying a steady-state markup for firms producing intermediate goods of 1.200. The Rotemberg parameter, which measures the costs of adjusting prices each period, has the following equivalence $\theta = p(\epsilon - 1)/[(1-p)(1-\beta p)]$, where $p \in [0, 1]$ denotes the probability of keeping the price unchanged; we set this probability to a standard value of 0.75, so the Rotemberg parameter takes the value of $\theta = 52.252$.

Next, we detail the estimated parameters for Mexico in the related literature. Montemayor (2000) estimates that the elasticity of public capital in the production function for Mexico is around 0.110 and 0.120, so we use the average value for the parameter $\gamma = 0.115$. For the public capital depreciation rate, we use the estimated value by Gutiérrez Cruz & Moreno Brid

(2022), which calculates that public capital depreciates annually at a rate of 9.7%. Therefore, the corresponding value to the parameter in our model is $\delta_G = 0.024$.

To obtain the parameter that measures the fraction of Ricardian households in the economy, we use the National Survey of Financial Inclusion (ENIF in Spanish), which indicates the percentage of households surveyed with at least one financial asset. The reports are only available for 2012, 2015, 2018 and 2021. The average for these years is 64%, so we set $\omega = 0.640$.

Before proceeding to the calibrated parameters, we first show the steady-state target values of our model. We assign the steady-state values for the output, productivity level, and shock in preferences of 1.000. We assume that households devote one-third of their time endowment to productive work, so we set the steady-state value of labor supply at 0.333. Next, we use annual data from the section of the Ministry of Finance and Public Credit (SHCP in Spanish), the National Institute of Statistics and Geography (INEGI in Spanish), and the Organization for Economic Cooperation and Development (OECD) for the period 2005 - 2023 to obtain the big ratios; these are government consumption, private sector gross fixed capital formation, public sector gross fixed capital formation, social spending, and public sector debt, all relative to GDP, the private consumption steady-state value is a residual. Subsequently, we compute the effective consumption tax rate using the Mendoza et al. (1994) methodology with OECD data.

Lastly, we describe the parameters calibrated to match the Mexican economy's big ratios obtained previously. We set the consumption tax rate to $\tau_C = 0.076$ to match the effective consumption tax rate obtained from the data. We calibrated the capital tax rate to match the private investment steady-state value of 0.181, so τ_K =0.084. On the other hand, we calibrated the payroll tax to match the public debt steady-state value of 1.469, so $\tau_L = 0.267$. We calibrated the fixed costs to match the normalized output steady-state value. Finally, we adjust the labor supply shock steady-state value to match the labor supply steady-state ratio. However, this value has a parameter dependency on the estimated elasticity of substitution between private and public consumption, obtained in the next section. Table 1.1 summarizes the parameter values obtained

Table 1.1: Calibrated parameters

Parameter	Value	Souce/Target
α, elasticity of private capital in production	0.333	
β, discount factor	0.990	
δ, private capital depreciation rate	0.025	RBC literature
φ, inverse of Frisch labor supply elasticity	1.000	
ϕ, private consumption weight	0.800	
ϵ, elasticity of substitution between varieties	5.000	NK literature
θ, price adjustment costs	46.602	
γ, elasticity of public capital in production	0.115	Montemayor (2000)
δ_G, public capital depreciation rate	0.024	Gutiérrez Cruz & Moreno Brid (2022)
ω, share of saver households	0.064	ENIF survey
Φ, fixed costs	0.026	Normalized steady-state output
τ_C, consumption tax rate	0.076	Effective consumption tax rate 7.6%
τ_K, capital tax rate	0.084	Private investment-to-GDP: 18.1%
τ_L, payroll tax rate	0.267	Quarterly debt-to-GDP: 190.0%

Source: Own elaboration

in this section.

1.3.2 Estimated parameters

In this section, we detail the Bayesian estimation process, where we construct seven observables for the estimation, given that the model has seven exogenous variables. The series shown in Table 1.2 were obtained for this purpose. The constructed observables are detailed below:

$$\Delta \ln (C_t) = 100 \times \left[\Delta \ln \left(\frac{738020}{446563}\right) - \overline{x}_1\right], \tag{1.29}$$

$$\Delta \ln (I_t) = 100 \times \left[\Delta \ln \left(\frac{738079}{446563}\right) - \overline{x}_3\right], \tag{1.30}$$

$$\Delta \ln (G_{C,t}) = 100 \times \left[\Delta \ln \left(\frac{738058}{446563}\right) - \overline{x}_2\right], \tag{1.31}$$

$$\Delta \ln (G_{I,t}) = 100 \times \left[\Delta \ln \left(\frac{738072}{446563}\right) - \overline{x}_4\right], \tag{1.32}$$

$$\ln \left(\frac{L_t}{L_{ss}}\right) = 100 \times \left[\ln \left(\frac{786468}{446563}\right) - \overline{x}_5\right], \tag{1.33}$$

Table 1.2: Reference series to construct observable variables

INEGI ID	Time-series	Units	Timespan
446563	Working age population	Millions of persons	2005/Q1-2023/Q4
738020	Private consumption	Millions of 2018 MXN	2005/Q1-2023/Q4
738079	Gross private fixed capital formation	Millions of 2018 MXN	2005/Q1-2023/Q4
738058	Government consumption	Millions of 2018 MXN	2005/Q1-2023/Q4
738072	Gross public fixed capital formation	Millions of 2018 MXN	2005/Q1-2023/Q4
786468	Total worked hours index	Base 2018 = 100	2005/Q1-2023/Q4
182022	Nominal interest rate	Annualized percentage	2005/Q1-2023/Q4
628194	Consumer Price Index	Base July 2018 = 100	2005/Q1-2023/Q4

Source: Own elaboration.
Notes: The consumer price index and nominal interest rate series are obtained from their source in monthly frequency, so we aggregate them quarterly using the corresponding months' average. In addition, together with the total worked hours index, they were adjusted for seasonality using X-13ARIMA-SEATS.

$$\frac{R_t}{R_{ss}} - 1 = 100 \times \left(\frac{182022}{400} - \overline{x}_6 \right), \tag{1.34}$$

$$\frac{\Pi_t}{\Pi_{ss}} - 1 = 100 \times \left[\Delta \ln \left(628194 \right) - \overline{x}_7 \right], \tag{1.35}$$

where, $\overline{x}_i$ denotes the respective data average; in other words, we demeaned data. Then, the parameters' prior probability distributions were obtained from related studies. We obtain the prior distribution for the elasticity of substitution between private and public consumption from Bušs & Grüning (2023). From Drygalla et al. (2020), we obtain the priors for the investment adjustment costs (ϑ), the Taylor rule coefficients (ρ_R, $\psi_{R,\Pi}$, $\psi_{R,Y}$), the reaction of different types of government spending to debt and output ($\psi_{C,D}, \psi_{I,D}, \psi_{T,D}, \psi_{C,Y}, \psi_{I,Y}, \psi_{T,Y}$), and the distributions associated with the standard deviations of the errors of the autoregressive processes ($\sigma_\chi, \sigma_R, \sigma_\xi, \sigma_A, \sigma_C, \sigma_I, \sigma_T$). Table 1.3 shows the details of each parameter's prior distributions and the results of the posterior estimates.

We use the Marco Ratto's `newrat` routine for mode search. Then, we use the Metropolis-Hastings random walk algorithm with two chains to obtain the posterior mean results. Finally, we use diagnostic tests to ensure MCMC chain convergence using 1,000 draws and discarding 30%. The proposal covariance matrix has been scaled to achieve an acceptance rate of roughly one third (32.91% and 32.97%).

Table 1.3: Estimated parameters

Parameters	Prior			Posterior	
	Dist.	Mean	S.D.	Mean	HPDI
ν, EoS private and public consumption	$\mathcal{G}$	0.900	0.100	0.679	(0.597, 0.758)
ϑ, capital adjustment costs	$\mathcal{N}$	6.000	1.500	6.432	(4.394, 8.486)
ρ_A, persistence technology shock	$\mathcal{B}$	0.800	0.050	0.945	(0.933, 0.958)
ρ_C, persistence government consumption shock	$\mathcal{B}$	0.800	0.050	0.890	(0.847, 0.933)
ρ_I, persistence public investment shock	$\mathcal{B}$	0.800	0.050	0.894	(0.856, 0.933)
ρ_T, persistence transfers shock	$\mathcal{B}$	0.800	0.050	0.867	(0.812, 0.921)
ρ_R, persistence monetary policy shock	$\mathcal{B}$	0.800	0.050	0.825	(0.796, 0.855)
ρ_ξ, persistence preference shock	$\mathcal{B}$	0.800	0.050	0.927	(0.900, 0.954)
ρ_χ, persistence labor supply shock	$\mathcal{B}$	0.800	0.050	0.946	(0.936, 0.956)
$\psi_{C,D}$, gov. consumption response to debt	$\mathcal{N}$	0.000	0.500	-0.596	(-0.846, -0.343)
$\psi_{I,D}$, public investment response to debt	$\mathcal{N}$	0.000	0.500	-0.133	(-0.823, 0.581)
$\psi_{T,D}$, transfers reaction to debt	$\mathcal{N}$	0.000	0.500	0.059	(-0.348, 0.474)
$\psi_{C,Y}$, gov. consumption response to output	$\mathcal{N}$	0.000	0.500	0.437	(0.120, 0.764)
$\psi_{I,Y}$, public investment reaction to output	$\mathcal{N}$	0.000	0.500	0.408	(-0.381, 1.180)
$\psi_{T,Y}$, transfers reaction to output	$\mathcal{N}$	0.000	0.500	0.715	(-0.018, 1.435)
$\psi_{R,\Pi}$, nominal interest rate reaction to inflation	$\mathcal{N}$	0.100	0.100	1.528	(1.392, 1.660)
$\psi_{R,Y}$, nominal interest rate reaction to output	$\mathcal{N}$	1.500	0.100	-0.048	(-0.065, -0.030)
σ_A, S.D. technology shock	$\mathcal{IG}$	0.100	2.000	1.188	(1.031, 1.344)
σ_C, S.D. government consumption shock	$\mathcal{IG}$	0.100	2.000	0.842	(0.725, 0.957)
σ_I, S.D. public investment shock	$\mathcal{IG}$	0.100	2.000	5.600	(4.805, 6.353)
σ_T, S.D. transfers shock	$\mathcal{IG}$	0.100	2.000	13.763	(10.059, 17.501)
σ_R, S.D. monetary policy shock	$\mathcal{IG}$	0.100	2.000	0.194	(0.163, 0.225)
σ_ξ, S.D. preference shock	$\mathcal{IG}$	0.100	2.000	1.834	(1.424, 2.223)
σ_χ, S.D. labor supply shock	$\mathcal{IG}$	0.100	2.000	7.221	(6.064, 8.354)

Source: Own elaboration.

Notes: Symbols $\mathcal{B}, \mathcal{G}, \mathcal{IG}, \mathcal{N}$ denotes Beta, Gamma, Inverse Gamma, and Normal distributions, respectively. HPDI denotes the High Posterior Density Interval. The log data density is -1001.71.

The results of the estimation of the elasticity of substitution between private and public consumption indicate complementarity between public and private goods, this value is slightly higher than that obtained by Bouakez & Rebei (2007), where they estimate an elasticity of substitution between private and public goods close to 0.300 for the economy of the United States, which indicates a greater degree of complementarity.

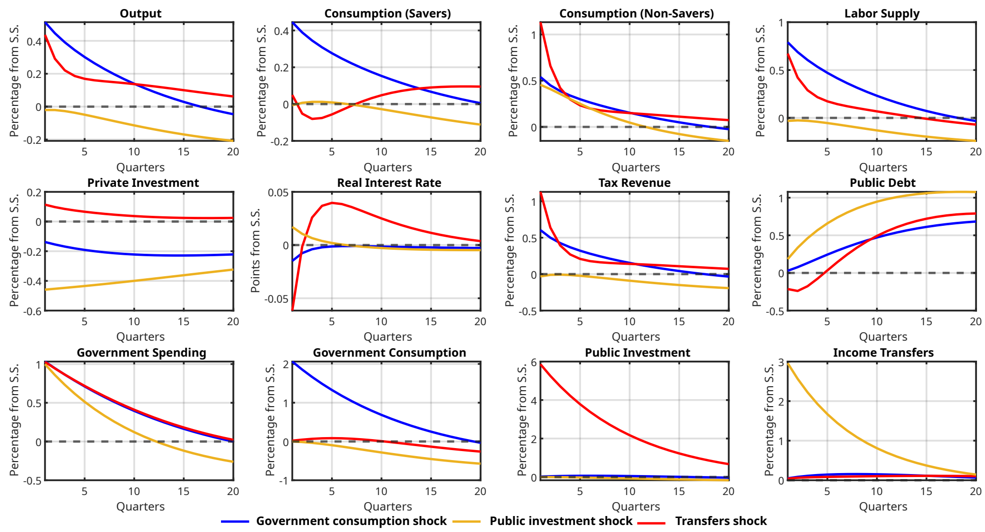
All the parameters of the autoregressive processes in fiscal policy exhibit a moderately high persistence in the posterior mean, ranging from 0.867 - 0.894. Regarding the systematic fiscal policy rules, estimates suggest that expenditure components respond positively to changes in output, indicating procyclical government spending. Bergman & Hutchison (2020), you have addressed this issue, which finds that in emerging economies, this is a common feature related to public investment expenditure, debt levels, and government efficiency, among other elements related to international trade. On the other hand, government consumption and public investment are the components with the greatest negative response to increases in debt, which implies that these elements tend to be reduced in fiscal consolidation policies.

Finally, regarding monetary policy estimates, they indicate that the nominal interest rate does not respond to the output gap solely to inflation, which is consistent with the current panorama of Mexico, where the central bank prioritizes the inflation objective.

1.4 Results

We detail the results section in two parts. First, we show how government spending instrument multipliers impact economic activity to illustrate this paper's proposed redistribution policy. Subsequently, we induce a recession through a demand shock as in Aursland et al. (2020) and compare three scenarios: no government intervention, increasing debt-financed government spending, and rising cut-financed government spending, and we compare the output and debt dynamics.

Figure 1.1: Fiscal policy impulse-response



1.4.1 Fiscal multipliers

We introduce fiscal shocks to evaluate the multiplier effect of spending instruments. The size of the shock of each instrument is such that it represents 1% of total government spending; this is to assess the impact of the same proportion of the fiscal budget allocated to the different fiscal policy instruments. Figure 1.1 shows this exercise's impulse-response functions (IRFs).

The IRFs reveal that allocating 1% of public spending to government consumption yields a greater impact on the output than spending the same amount on other components individually. This effect operates through the following transmission mechanism: an increase in government consumption spending, driven by fiscal policy, increases household demand for private goods due to their complementarity. Consequently, households are motivated to improve their labor supply to enhance their income. In response, firms ramp up production to meet the rising demand from households and the government, resulting from this fiscal policy. On the other hand, this policy does not collect enough tax to compensate for the increase in public spending. Therefore, public debt increases.

On the other hand, public investment also positively impacts the product. Although this effect is smaller than government consumption shock, it is more persistent. This aligns with the findings of Junior et al. (2016), who argue that private investment has a greater long-term impact. This policy positively affects private investment, compelling saving households to reduce their short-term consumption. On the other hand, as firms observe increased production, the labor demand increases. Therefore, non-saving households work more hours, thus generating higher income, which they allocate to their consumption. Due to investment adjustment costs, this policy takes time to impact the product significantly. The increase in consumption, employment, and investment derived from this exercise causes tax revenue to increase more than the increase in spending, so the public debt decreases in the short term. However, after five quarters, the public debt begins to increase gradually.

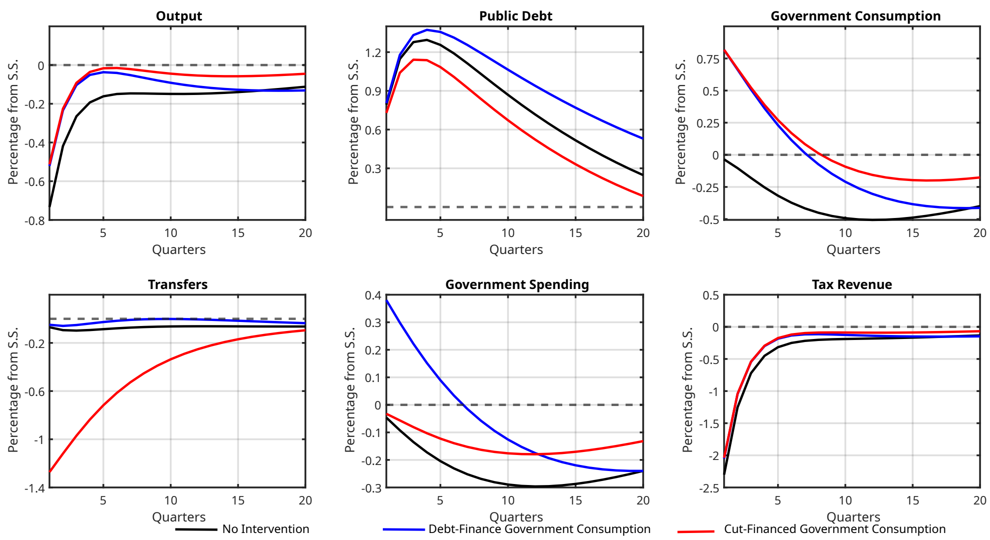
The increase in transfers causes households to increase their consumption in the short term. The effect on non-saving households is greater, which causes them to reduce their labor supply, weakening production. Since economic activity is affected, tax revenue decreases considerably. Therefore, carrying out this policy generates greater debt than in previous years.

1.4.2 The impact of fiscal policy in the face of a recession

We evaluate the impact of a recession triggered by a decrease in aggregate demand (negative preference shock) under three scenarios. The first scenario considers the effect without any government intervention. The second scenario examines government intervention, where the highest multiplier government spending component is financed through increased debt. The third scenario explores government intervention by reallocating funds: financing the highest multiplier government spending component by reducing expenditure on the lowest multiplier government spending instrument, thereby minimizing the impact on public debt.

In the scenario without government intervention, we assume that fiscal instruments adhere strictly to their systematic components, and we introduce a preference shock equivalent to one standard deviation. Again, we introduce the same preference shock in the scenario involving

Figure 1.2: The role of fiscal policy



fiscal stimuli financed through public debt. Additionally, we incorporate a government consumption shock of one standard deviation, as this component has the highest multiplier effect on output. Finally, we introduce a negative transfer shock to balance the increase in government consumption. This approach aims to offset the rise in government consumption, ensuring that fiscal intervention does not exacerbate public debt. The results of this exercise are shown in Figure 1.2 and are described below.

We observe that government intervention alleviates the impact of the recession in both scenarios. However, intervention financed through increased public debt incurs significant costs to public finances. Conversely, a policy financed by reallocation, specifically cutting lower multiplier public spending to fund higher multiplier spending, effectively mitigates the recession's impact while also serving as a fiscal consolidation strategy. This approach, however, involves trade-offs, including potential reductions in social spending.

1.5 Conclusion

In this study, we estimate a New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) model for the Mexican economy to evaluate the impact of fiscal policy on recessions under different financing methods. Our findings reveal that government consumption has the most significant positive impact on economic activity, whereas transfers negatively affect production. Additionally, these effects contribute to the accumulation of public debt.

We then assess the impact of a recession induced by a demand shock across three scenarios: without fiscal stimuli, with fiscal stimuli financed through debt, and with fiscal stimuli financed by spending cuts. Our analysis shows that the policy based on spending cuts stimulates economic activity and simultaneously acts as a fiscal consolidation measure, which has favorable implications for long-term public finances.

Our results suggest a viable strategy for governments facing instability in their public finances and seeking to stimulate economic activity. However, this approach involves social costs, particularly impacting households that rely heavily on daily income (non-savers), as transfers constitute a significant portion of their earnings. This, in turn, may generate political pressure due to potential voter dissatisfaction, which could deter governments from implementing cuts to social spending.

The viability of the cutback financing policy proposed in this study faces significant challenges in timely implementation. Eguchi et al. (2024) noted that changes in fiscal policy, unlike monetary policy, require more time to enact. This delay is due to the necessity of presenting decisions to a legislative body where they are debated and may ultimately be rejected or modified, delaying or preventing their execution.

Our study presents several limitations that can be addressed in future research. For instance, the model does not account for the effects of the informal sector, which plays a significant role in the Mexican economy. The impact of fiscal policy, particularly the multipliers, is influenced by this sector, as suggested by Colombo et al. (2024). Additionally, the model does not consider the external sector's impact. Previous studies, such as those by Varthalitis (2019); Ilzetzki et al. (2013); Bergman & Hutchison (2020), among others, indicate that the size of fiscal multipliers is related to the degree of trade openness. Lastly, given that Mexico is an oil-exporting country, future models could incorporate the impact of oil revenues on the government's budget constraint.

Chapter 2

The Role of Informality in the Economic Growth, Employment, and Inflation During the COVID-19 Crisis

2.1 Introduction

The COVID-19 pandemic in 2020 has caused the largest global economic contraction in the last 60 years. According to World Bank data, the world GDP per capita contracted by 4.0% from a year earlier, and the employment rate fell by 1.8 pp. In addition, one year later, global inflation increased by 3.5%, among the largest increases in the last decade. These increases in global prices are due to substantial interruptions in the global supply chain, changes in household consumption patterns, and frictions in the labor markets, which made it impossible to satisfy the demand derived from the progressive economic reopening (see Kouvavas et al. (2020); Boissay et al. (2021); LaBelle & Santacreu (2022)).

The pandemic has affected each country differently. The handling of the pandemic by the authorities, the stimulus policies of the governments, and some structural characteristics of the countries, such as economic diversification, the structure of the labor market, and the educational level, explain these differences (see Galasso & Foucault (2020); Gimbel et al. (2020); Niermann & Pitterle (2021); Leyva & Urrutia (2022)). In particular, the Latin America and Caribbean (LAC) region was the most affected regarding economic growth and employment rate. Despite this, it was one of the regions with the least changes in the inflation rate.

Regarding the labor market structure, LAC countries stand out for their large informal sectors David et al. (2020). This labor market structure is vital to its resilience during the COVID-19 pandemic. On the one hand, Loayza (2020) argues that informal employment is a characteristic of emerging and developing economies that makes them more vulnerable to the COVID-19 crisis. On the other hand, Alberola & Urrutia (2020) demonstrates that the informal sector acts as a buffer against inflationary pressures caused by various shocks, including those related to demand, technology, monetary policy, and financial markets, where the coronavirus crisis is a combination of these shocks.

In the pandemic crisis, the informality rate in the LAC region showed unprecedented procyclical behavior. Leyva & Urrutia (2022) documented and explained this fact. In particular, these authors found that labor supply and productivity shocks in the informal sector explain the procyclical informality rate and the large economic and employment losses during the pandemic. However, the Leyva & Urrutia 's (2022) model presents some limitations that prevent us from ascertaining the role of the informal sector during the COVID-19 crisis. First, productivity and labor supply shocks are treated as pandemic shocks. At the same time, recent works such as Busato et al. (2021) introduce a richer pandemic environment that allows a better simulation of the COVID-19 crisis, including a lockdown policy based on active cases and economic activity instead of treating the pandemic shock as a combination of a productivity shock and a labor supply shock. Second, a framework of nominal rigidities, typical of a New Keynesian Dynamic Stochastic General Equilibrium (NK DSGE) model, is not considered, making it almost impossible to assess the inflationary effects of the pandemic crisis.

In this study, we explore the role of the informal sector in three main macroeconomic aggregates: the output growth rate, the employment rate, and the inflation rate, in the face of shocks that simulate the COVID-19 crisis. We use the framework of Busato et al. (2021), which provides a detailed pandemic block and endogenous lockdown policy. In addition, on the demand side, we add a factor that decreases both the marginal utility of consumption and labor supply with the severity of the disease, similar to Chan (2022). Finally, we introduce a rich labor market structure, and nominal rigidities, as in Alberola & Urrutia (2020). The exercise introduces an exogenous virus outbreak under two cases, an economy with mixed employment and another with the same characteristics but without informal employment. This counterfactual exercise allows us to determine the effect of the shadow economy on the pandemic crisis.

Following Fernández & Meza (2015); Leyva & Urrutia (2020); Alberola & Urrutia (2020), we calibrate the model for Mexico's economy as a potential representative of the informal economy in the LAC region, given its high rates of informality and the wide availability of data related to employment and the pandemic. First, we obtain the structural parameters from Alberola & Urrutia 's (2020) model, the equivalent case to the pre-pandemic economy. Subsequently, we adjust the model to a fortnightly frequency. For this, we adjust the value of some parameters that allow us to simulate the dynamics under this frequency. Finally, we calibrate the parameters related to the COVID-19 block, using data on new cases and deaths from COVID-19 for the Mexican economy from the second half of February 2020 to the second half of June 2021. Even though the analysis focuses on the 2020 - 2021 period, to avoid distortions in the macroeconomic aggregates due to the Russian invasion of Ukraine, we take the most recent data from the pandemic, which allows us better to model the behavior of the virus outbreaks in Mexico.

The model operates as follows. First, there is an outbreak of an exogenous virus that spreads among individuals through consumption, labor, and non-economic activities. So, the active cases start to pile up as some recover and others die. At the same time, the government implements the lockdown policy by limiting the effective use of labor through a policy rule that depends on the mortality rate, preventing the further spread of the virus and human losses. Later, as the virus spread slows, the death rate begins to decline, allowing the government to relax lockdown measures and leading the economy into a recovery stage. Finally, households recover the path of consumption and rejoin the labor market.

In our simulations, a single virus wave (a pandemic shock) produces strong economic and job losses, large and persistent price increases, and a procyclical informality rate consistent with the dynamics observed during the COVID-19 crisis. By removing informal employment from the benchmark model, we find that the pandemic shock in this economic environment causes less economic and employment damage; however, it produces greater inflationary effects. In addition, the recovery of total employment is slower than when the labor market is mixed, and this is because informal employment is frictionless, allowing it greater resilience during the economic reopening.

We also break down the characteristics of the informal sector one by one to identify how they individually contribute to the impacts of the pandemic crisis. We find that the main features are free entry costs and tax evasion. On the one hand, free entry costs accelerate the flows into and out of informal employment, which produces greater falls in total employment and output at the time of the pandemic shock, and in the recovery phase, the economy does so faster. On the other hand, tax evasion prevents the government from alleviating the economy through lump-sum taxes since it reduces them less than in a scenario where informal employment is absent, which prevents households from smoothing their consumption. Therefore, a buffering effect over inflation arises.

Finally, through a welfare analysis, our results indicate that welfare loss in an economy without the informal sector is less than when there is mixed employment. This result highlights the consequences of lockdown policies in economies with large informal sectors and the challenges to labor market regulation in the Latin American and Caribbean region.

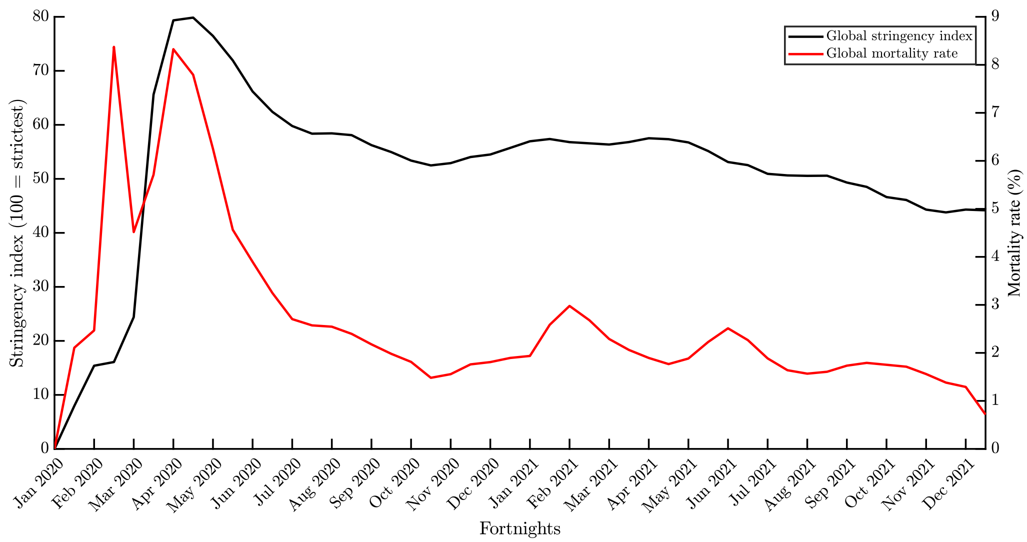
The rest of this document is organized as follows. Section 2.2 presents a review of the COVID-19 crisis in the world with an emphasis on the Latin American and Caribbean region and their labor market structure. The literature review is shown in Section 2.3. Next, Section 2.4 describes the structure of the model, while Section 2.5 details the calibration of the parameters. Section 2.6 discusses the research results, the impulse response functions, and the counterfactual exercise that eliminates informal employment. Section 2.7 concludes.

2.2 Background

The first human cases of COVID-19, the Coronavirus disease caused by SARS-CoV-2, occurred in Wuhan Province, China, in December 2019. During the first quarter of 2020, the virus spread to all continents, infecting over 850,000 people and causing 450,000 deaths. As a result, the World Health Organization declared the novel Coronavirus outbreak a global pandemic.

Policymakers implemented restrictive lockdown measures to hold back the spread of the virus and prevent further human losses at the cost of stopping the world economy Leyva & Urrutia (2022). The main measures consisted of quarantines, travel restrictions, factory closures, limited

Figure 2.1: Lockdown vs. Mortality rate



personnel, and severe limitations in the service sector Boone et al. (2020). Hence, the labor market suffered a major shock, leading to a deep global economic contraction. In return, the global mortality rate was reduced, which allowed the confinement measures to be relaxed (see Figure 2.1). Subsequently, however, an inflationary worldwide phenomenon arose since the strong disruptions in the global supply chain and the lack of labor input made it impossible to satisfy the increase in demand resulting from the economic reopening.

The coronavirus crisis affected world regions unequally (see Table 2.1). The heterogeneity in the ravages of the crisis is explained by governments' different handling of the pandemic, both in terms of health, fiscal, and monetary policy (see, for example, König & Winkler (2021); Chen et al. (2021); Yilmazkuday (2022)). In addition, the economic characteristics of each country, such as the labor market structure and economic diversification, contribute to widening these differences (see Niermann & Pitterle (2021), and Leyva & Urrutia (2022)).

LAC region was the most affected group in terms of economic growth and employment rate; despite this, the price increase was not even among the three highest (see Table 2.1). Concerning the topics that highlight the difference in the impact of COVID-19 between countries, the LAC region stands out for its labor market structure, which, according to David et al. (2020), is char-

Table 2.1: Main macroeconomics aggregates during COVID-19 pandemic

Group	GDP growth rate (2019 - 2020)	Δ Employment rate (2019 - 2020)	Inflation rate (2020 - 2021)
(a) Income level			
High income	-4.6	-1.9	2.5
Upper middle income	-1.2	-2.2	3.5
Middle income	-2.2	-1.9	4.1
Lower middle income	-4.5	-1.4	3.5
Low income	-2.7	-1.2	5.0
(b) Region			
East Asia and Pacific	-0.6	-1.6	2.4
Europe and Central Asia	-5.7	-1.2	3.3
Latin America and Caribbean	-7.4	-5.0	3.9
Middle East and North Africa	-5.1	-1.7	2.3
North America	-3.9	-4.0	4.0
South Asia	-5.7	-1.3	5.5
Sub-Saharan Africa	-4.5	-1.0	4.3
(c) Other			
OECD members	-4.7	-2.4	2.8
World	-4.0	-1.8	3.5

Source: Author's calculations with data from World Bank Data.
Note: The figures in the first and third columns represent percentages, while in the second column, they represent percentage points.

acterized by large informal sectors and relatively rigid labor regulation. Furthermore, according to Elgin et al. (2022), the size of the informal economy is strongly related to the effectiveness and size of the fiscal stimulus, which contributes to the explanation of the differences in the impact of the COVID-19 crisis.

By 2019, in more than half of the LAC countries, informal employment represents more than half of the total employment (see Table 2.2). Moreover, according to Medina & Schneider (2019), LAC is the second region where the informal economy contributes a high percentage of GDP, behind Sub-Saharan Africa. In addition, Leyva & Urrutia (2022) mention that in previous downturns, Mexico, Colombia, Brazil, and Chile exhibited a countercyclical informality rate. However, during the pandemic slump, it had a procyclical behavior. Therefore, it is worth analyzing the effects of informal employment in the LAC region.

Table 2.2: Informality rate in the Latin American and Caribbean countries during 2019

Country	Informality rate	Country	Informality rate
Uruguay	24.5	Venezuela	58.3
Chile	29.3	Barbados	62.0
Saint Lucia	31.9	Colombia	62.1
Brazil	40.1	Ecuador	63.5
Costa Rica	41.2	Peru	68.4
Argentina	49.7	Paraguay	68.9
Guyana	50.0	El Salvador	69.1
Suriname	52.1	Guatemala	79.0
Panama	52.8	Bolivia	81.5
Dominican Republic	54.2	Nicaragua	81.8
Jamaica	56.4	Honduras	82.6
Mexico	57.6	Haiti	91.6

Source: Author's calculations with data from International Labour Organization.
Note: We use the most recent informality rate available for Suriname, Venezuela, Barbados, Nicaragua, Honduras, and Haiti.

2.3 Literature review

The emergence of the COVID-19 pandemic attracted the attention of academics, who began investigating its impact on health and the economy. Among the first studies is the work of Atkeson (2020), which uses the SIR (Susceptible-Infected-Recovered) epidemiological model, initially proposed by Kermack & McKendrick (1927), to simulate the dynamics of COVID-19 and emphasizing the importance of social distancing, since this measure allows flattening the contagion curves.

The work of Eichenbaum et al. (2021) was one of the pioneers in embedding the SIR epidemiological model into a DSGE macroeconomic model, thus simulating the economic consequences of the COVID-19 pandemic. This model assumes that people can assimilate the disease risk and decide to cut their consumption and reduce the labor supply, causing great economic damage. On the other hand, Busato et al. (2021) uses a similar approach, assuming that the government induces a lockdown policy based on forcibly reducing firms' labor utilization, leading the economy into a recession. This analysis considers three scenarios: the government is more concerned about health, is indifferent between health and the economy, or is more concerned about the economy. Therefore, the government's preferences in dealing with the pandemic play an important role in the size of the recession.

The two studies above implicitly explain the differences in employment rates and economic growth between countries or regions through the differences in the disease risk perception and the lockdown policy's intensity. These two effects operate through reductions in aggregate demand (consumers react to risk by reducing consumption) and reductions in aggregate supply (workers react to risk by reducing their labor supply, and the government forces firms to quarantine their employees). However, these studies do not consider an environment with nominal rigidities that make it possible to assess the inflationary pressures of the pandemic crisis.

In line with the above Eichenbaum et al. (2022) extend the model of Eichenbaum et al. (2021), introducing nominal rigidities. In the first place, they compare the model with flexible prices and those with sticky prices, which yield similar results except in the rate of inflation and investment. The model with sticky prices presents more of a moderate decrease in the inflation rate but a severer drop in investment. Second, they find that the inflation rate declines after the virus outbreak and levels off a year later in both models. However, as we have mentioned before, during the second year of the pandemic in most regions of the world, inflation did not stabilize; on the contrary, large price increases were observed.

He & Wang (2022) also feed their model with nominal rigidities. Still, unlike the previous models, they treat the pandemic crisis as a combination of a technological shock and a shock that affects the labor force, that is, from the aggregate supply side. The result they obtain in terms of the inflation rate is that it increases after the economy is disturbed by the pandemic shock since the labor force decreases and production costs increase. In addition, they mention that monetary and fiscal policy can alleviate job losses and increase production to some extent, but long-term inflationary pressures accompany monetary policy.

Therefore, the perceptions of contagion risk, the strictness of the lockdown policy, the fiscal packages, and the monetary policy play an important role in the impact of the pandemic on the economic growth rate, the employment rate, and the inflation rate. However, for the LAC region, Niermann & Pitterle (2021) mention that the restrictions were as severe as in many other regions; furthermore, fiscal incentives per capita represented 8% of GDP, a value that remains slightly below the average in the groups of countries considered by the authors. On the monetary policy side, there are significant differences between advanced and emerging countries, according to Yilmazkuday (2022), since emerging countries were able to respond to reductions in economic activity by reducing interest rates more aggressively. In contrast, the advanced countries did not act similarly to the emerging countries since most of them have zero-bound on their interest rates. Despite these differences in monetary policy between advanced and emerging economies, we find no evidence that the countries of the LAC region have deployed expansionary monetary policies more aggressively to combat the pandemic crisis than the rest of the emerging economies.

One characteristic that stands out in the Latin American and Caribbean region is its high level of informality, whose role in the COVID-19 crisis has been explored very little. Loayza (2020) argues that informal employment makes economies more vulnerable to the coronavirus crisis. The study of Leyva & Urrutia (2022) seeks to replicate the procyclical behavior of the informality rate in the LAC region during the pandemic crisis through a DSGE model; they use technology and labor supply shocks to simulate the behavior of the crisis. However, the model lacks epidemiological modeling and nominal rigidities. In addition, the role of the informal economy in the main economic aggregates during the COVID-19 crisis is not investigated.

Alberola & Urrutia (2020), through a counterfactual exercise in a DSGE model, find that the presence of the informal sector facilitates price stabilization in the face of demand, technology, and monetary and financial shocks. Furthermore, employment and output contract less in the model with informality than in the model without because of productivity and financial shocks in the formal sector. In most cases, the informality rate acts countercyclically, except for aggregate demand and supply shocks. However, their analysis does not consider a pandemic shock that allows for addressing the role of informality in the COVID-19 crisis.

In this sense, the contribution of this work to the economic literature is to emphasize the role of the informal economy in the face of an economic crisis induced by forced confinement, paying special attention to the main macroeconomic aggregates. For this purpose, we use the Alberola & Urrutia 's (2020) model, which presents a detailed environment of the labor market with frictions and rigidities in prices, and we embed epidemiological modeling similar to Busato et al. (2021). In addition, given the relationship between the lockdown policy and the mortality rate presented in the stylized facts, we add a lockdown policy rule that reacts to the virus mortality rate. In the next section, we present the model in detail.

2.4 Model

This section presents a parsimonious DSGE model for a closed pandemic economy with a representative household, formal and informal productive sectors, labor market frictions, nominal rigidities, and a central government that oversees fiscal, monetary, and health policies.

The representative household may spend part of its time working in the formal sector. It may also be self-employed in the informal sector[1], seek formal jobs as unemployed, or stay out of the labor force. Following Alberola & Urrutia (2020), we characterized the formal labor market as a sector with frictions in the hiring process, participation in the credit market, and contributing with taxes to the government; on the other hand, the informal sector operates with low productivity, is more flexible, evades taxes, and its members do not have access to the credit market.

Virus outbreaks occur exogenously, while their spread occurs through consumption, labor, and non-economic activity. In addition, the cases remain active for about a fortnight, some recover,

[1] Alberola & Urrutia (2020) assume that the informal sector is composed entirely of self-employed workers since, in Mexico, 41% of informal workers are self-employed. While in the formal sector, the self-employed represent 14%.

and others die from the disease.

The government manages monetary policy by setting the interest rate according to a Taylor-type feedback rule on inflation and the output gap. The fiscal policy collects fixed and payroll taxes to finance public spending. Finally, health policy operates through restrictions on the use of labor following the mortality rate and the output gap.

2.4.1 Population, occupation, and households

The total population is standardized to one and split into four occupational groups: individuals employed in the formal sector denoted by L_t^F, those who are self-employed represented by L_t^S, unemployed people indicated by U_t, and individuals who are not part of the labor force and denoted by O_t. The non-employed category is further classified into two groups: the unemployed, who incur job search costs, and those who are inactive. Finally, the total labor supply is the sum of individuals employed in the formal sector and those self-employed, represented by L_t.

The representative household derives utility from consumption and disutility from both labor and unemployment. Labor disutility is interpreted as the value of foregone leisure, while unemployment disutility is related to job search costs. The expected lifetime utility function is given by:

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t H_t \left[\log \left(C_t - \psi \Phi_t \frac{L_t^{1+\phi}}{1+\phi} \right) - \frac{\varsigma}{2} U_t^2 \right], \tag{2.1}$$

where $\mathbb{E}_t$ denotes the mathematical operator of expectations conditional on the information available in period t, C_t and L_t are consumption and labor supply at time t, N_t are the new cases of the disease. $\beta \in (0,1)$ is the subjective discount factor, $\psi \in [0,\infty)$ measures the labor disutility, $\phi \in (0,\infty)$ is the inverse of Frisch elasticity, $\varsigma \in (0,\infty)$ measures the cost of searching for unemployment. Following Chan (2022) H_t is a health-related variable that affects consumption desire, and the disutility of both labor and unemployment has the following behavior:

$$H_t = \left(\frac{N_t}{N_{ss}} \right)^{-\varphi_h} \tag{2.2}$$

where $\varphi_{h,c} \in [0, \infty)$ denotes the percentage increase in H_t for a 1% increase in infected; therefore, higher infection rates elevate fear of contagion, leading households to reduce consumption and work hours as preventive measures. A deterministic shifter factor is introduced $\Phi_t \equiv C_t^{\omega} \Phi_{t-1}^{1-\omega}$ that allows controlling the wealth effect on the labor supply by varying the parameter $\omega \in [0, 1]$.

Household expenses are distributed in consumption, physical capital investment, and the purchase of domestic bonds. At the same time, the sources of income are labor income from the formal and informal sectors, income from capital returns from holding bonds, profits from the firms they own, and direct taxes. Therefore, the household budget constraint in real terms is given by:

$$C_t + I_t + B_t \leq W_t^F \mu_t L_t^F + W_t^S \mu_t L_t^S + R_t K_t + \left(\frac{1 + i_{t-1}}{1 + \pi_t} \right) B_{t-1} + \Pi_t - T_t, \tag{2.3}$$

where I_t is the capital investment, B_t are domestic bonds, W_t^F is the wage per unit of effective labor in the formal sector, W_t^S is the wage per unit of effective labor in the informal sector, R_t represents the rate of rent for capital, K_t is the capital stock, i_t is the nominal interest rate, π_t denotes the inflation rate, Π_t represents profits from firms owned by the household, T_t is a lump-sum tax, and μ_t denotes the labor effective utilization.

The latter is a time-varying parameter that seeks to capture the strength of social distancing measures. Higher values indicate minimal social distancing (e.g., a value of one implies no confinement measures), while values closer to zero represent stricter quarantine measures. We'll delve deeper into this concept later.

Additionally, the investment decisions are affected by convex capital adjustment costs, and the physical capital is accumulated according to the following law of motion:

$$K_{t+1} = (1 - \delta) K_t + I_t - \frac{\vartheta}{2} \left(\frac{I_t}{K_t} - \delta \right)^2 K_t, \tag{2.4}$$

where $\delta \in (0,1)$ measures the capital depreciation rate, and $\vartheta \in [0,\infty)$ captures the sensitivity parameter for the capital adjustment costs.

2.4.2 Firms

Final good firms. The final good is aggregated across varieties, $z \in (0,1)$, of the intermediate goods using a Dixit-Stiglitz aggregator:

$$Y_t \equiv \left(\int_0^1 Y_t\left(z\right)^{\frac{\eta-1}{\eta}} dz \right)^{\frac{\eta}{\eta-1}}, \tag{2.5}$$

$\eta \in [0,\infty)$ is a parameter that measures the elasticity of substitution between varieties. The profits of the final good distributor are given by:

$$P_t Y_t - \int_0^1 P_t\left(z\right) Y_t\left(z\right) dz, \tag{2.6}$$

where P_t is the price of final good and $P_t(z)$ is the price associated with the variety z. The distributor of the final good maximizes his profits by choosing the quantity of the final good while taking the price of the final good and the varieties as given.

Intermediate goods firms. There are a continuum of intermediate good firms indexed by $z \in (0,1)$. Each intermediate good firm z solves a two-step problem to produce a variety z. In the first step, it minimizes its cost by selecting capital stock $K_t\left(z\right)$, and the quantities of formal $Q_t^F\left(z\right)$ and informal goods $Q_t^S\left(z\right)$,

$$R_t K_t\left(z\right) + P_t^F Q_t^F\left(z\right) + P_t^S Q_t^S\left(z\right), \tag{2.7}$$

where P_t^F is the price of goods produced in the formal sector and P_t^S is the price of goods produced in the informal sector, taking prices as given subject to the production function:

$$Y_t(z) = A_t\left[\alpha K_t(z)^{\frac{\nu-1}{\nu}} + (1-\alpha)\, Q_t(z)^{\frac{\nu-1}{\nu}}\right]^{\frac{\nu}{\nu-1}}, \tag{2.8}$$

here A_t denotes total factor productivity (TFP), $\alpha \in (0,1)$ is a distribution parameter reflecting capital intensity in production. The composite good is defined as follows:

$$Q_t(z) = \left(Q_t^F(z)^{\frac{\epsilon-1}{\epsilon}} + Q_t^S(z)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}, \tag{2.9}$$

where $\epsilon \in [0,\infty)$ is the elasticity of substitution between formal and informal goods. The formal good is produced using effective labor from the formal sector. In contrast, the informal output is produced using effective labor from the informal sector, that is, $Q_t^F(z) \equiv A_t^F \mu_t L_t^F(z)$ and $Q_t^S(z) \equiv \chi \mu_t L_t^S(z)$, where A_t^F denotes the productivity of a worker in the formal sector, and $\chi \in [0,1]$ captures inefficiencies in informal sector productivity relative to formal sector productivity.

In the second step, only a random fraction $1-\theta$ of firms can reset their price; all other firms keep their prices unchanged. When firms reset their prices, they must consider that the price may be fixed for many periods. The following problem gives the optimal price selection. Each monopolistic firm z chooses its price $P_t^*(z)$, to maximize its nominal profits facing Calvo-type nominal rigidities and a common marginal cost MC_t:

$$\mathbb{E}_t \sum_{j=0}^{\infty} (\theta\beta)^j \frac{\lambda_{C,t+j}}{\lambda_{C,t}} \left(\frac{P_t^*(z)}{P_{t+j}} - \frac{MC_{t+j}}{P_{t+j}}\right) Y_{t+j}(z), \tag{2.10}$$

subject to the aggregate demand condition from the final good maximization problem:

$$Y_t(z) = \left(\frac{P_t(z)}{P_t}\right)^{-\eta} Y_t. \tag{2.11}$$

On the other hand, under the assumption of symmetry in which all firms follow the same pricing strategy, aggregating among retailers, the aggregate price index is given by:

$$P_t = \left[(1-\theta) P_t^{*1-\eta} + \theta P_{t-1}^{1-\eta} \right]^{\frac{1}{1-\eta}} . \tag{2.12}$$

2.4.3 The labor market

There is a continuum of ex-ante equal formal entrepreneurs indexed by $f \in (0,1)$ with the potential to start a firm. Meanwhile, unemployed individuals U_t are looking for formal employment, and the entrepreneurs are creating job opportunities by posting formal job vacancies V_t^F. New formal matches are created through a standard constant return to scale matching function as follows:

$$M_t(f) = U_t(f)^{\zeta} V_t^F(f)^{1-\zeta} , \tag{2.13}$$

where $\zeta \in (0,1)$ is the matching function elasticity. A vacancy has a common cost $\xi \in [0,\infty)$, which lasts a period and is expressed in units of the final good for the entrepreneur.

At the beginning of the period, a group of workers $L_{t-1}^F(f)$ are employed in the formal sector. A certain exogenous fraction $s \in (0,1)$ of the employed workers are laid off and unemployed. During the period, new formal matches between firms and workers are also created, so the number of formal employees at time t evolves by:

$$L_t^F(f) = (1-s) L_{t-1}^F(f) + q_t^F(f) V_t^F(f) , \tag{2.14}$$

where $q_t^F(f)$ represents the probability that a vacancy is filled by a worker and is determined by the first-order condition of the matching function with respect to vacancies.

An active match produces one unit of formal intermediate input using one worker. The value of a match for a formal entrepreneur in terms of utility is defined recursively as follows:

$$J_t^F = \mu_t \left[P_t^F A_t^F - (1 + \kappa i_t + \tau) W_t^F\right] \lambda_t^C + \beta (1 - s) \mathbb{E}_t J_{t+1}^F, \tag{2.15}$$

where $\kappa \in (0, \infty)$ represent the working capital requirement for the formal sector and $\tau \in (0, 1)$ is a payroll tax.

On the other hand, the value that a worker assigns to being employed in the formal sector is represented by λ_t^F and is given recursively by:

$$\lambda_t^F = \mu_t W_t^F \lambda_t^C - \psi \Phi_t L_t^\phi \frac{\partial u_t}{\partial C_t} + \beta (1 - s) \mathbb{E}_t \lambda_{t+1}^F, \tag{2.16}$$

here $\partial u_t / \partial C_t$ denotes the marginal utility of consumption and λ_t^C represents the Lagrange multiplier for consumption.

The Nash product is defined as the weighted product of the value of a single worker for a formal employer and the value of a formal job for a worker as follows:

$$\left(\lambda_t^F\right)^\gamma \left(J_t^F\right)^{1-\gamma}, \tag{2.17}$$

where $\gamma \in (0, 1)$ represents workers' bargaining power. The wage in the formal sector is determined by the argument that maximizes the Nash product. Finally, vacancy postings in the formal sector satisfy the following zero profit condition:

$$q_t^F J_t^F = \xi \lambda_t^C. \tag{2.18}$$

The informal sector has no search frictions, taxes are evaded, and no access to working capital (see equation (25)), so the representative household determines wages and informal labor.

2.4.4 COVID-19 pandemic

The transmission of virus V_t occurs in the workplace, consumer activities, and non-economic activities, so that the following expression gives the newly infected N_t:

$$\frac{N_t}{N_{ss}} = (\varpi_c C_t + \varpi_l \mu_t L_t + \varpi_o)\, V_t, \tag{2.19}$$

where $\varpi_c, \varpi_l, \varpi_o \in [0, \infty)$ are the consumption, labor, and non-economic activity weight in epidemic propagation, respectively.

The size of the disease S_t is determined by the current patients, the new cases, less the recovered ones, and the deaths; this is expressed through the following accumulation rule:

$$S_{t+1} = (1 - r - m)S_t + N_t, \tag{2.20}$$

where $r \in (0, 1)$ is the recovery rate and $m \in (0, 1)$ denotes the mortality rate mean.

2.4.5 Government

The government oversees the fiscal, monetary, and health policies. The monetary policy is executed by adjusting the nominal interest rate based on a Taylor-type feedback rule, which considers inflation and the output gap.

$$1 + i_t = \frac{1}{\beta} \left(\frac{P_t}{P_{t-1}} \right)^{\varphi_{i,\pi}} \left(\frac{Y_t}{Y_t^n} \right)^{\varphi_{i,y}}, \tag{2.21}$$

where $\varphi_{i,\pi} \in [0, \infty)$ is the parameter that governs the reaction of the interest rate to inflation, and $\varphi_{i,y} \in [0, \infty)$ captures the reaction of the interest rate to the output gap.

On the other hand, fiscal policy encompasses the collection of taxes and the exercise of public spending. Public spending G_t follows the output[2], so the exercise of spending is carried out as

[2]The assumption that public spending is a fraction of output supports a procyclical fiscal policy observed in

a stochastic fraction g_t of the output $G_t = g_t Y_t$. The government budget constraint is given by:

$$G_t = \tau W_t^F \mu_t L_t^F + T_t, \tag{2.22}$$

Finally, on the health policy side, the government restricts the use of labor in the formal and informal sectors indiscriminately when there are sharp increases in the death rate from the disease, and at the same time, is concerned about the damage to the economy; therefore it also takes into account the output gap:

$$1 - \mu_t = (1 - \mu_{t-1})^{\rho_\mu} \left[\left(\frac{S_{t+1}}{S_{ss}} \right)^{\varphi_{\mu,s}} \left(\frac{Y_t}{Y_t^n} \right)^{1-\varphi_{\mu,s}} \right]^{1-\rho_\mu}, \tag{2.23}$$

here the use of labor μ_t is controlled by the government simulating the lockdown policy; this component reacts negatively to increases in active cases of the disease and to the output gap in an exchange between health and the economy, where $\rho_\mu \in (0, 1)$ measures the persistence of lockdown policy, and $\varphi_{\mu,s} \in [0, 1]$ is the elasticity of the lockdown policy to the active cases.

2.4.6 Market clearing

The aggregate profits of formal entrepreneurs are given by the earnings from the sale of formal inputs minus the capital requirements of formal workers, wages, and the cost of posting vacancies, that is:

$$\Pi_t^F = P_t^F Q_t^F - (1 + \kappa i_t + \tau) W_t^F \mu_t L_t^F - \xi V_t^F, \tag{2.24}$$

On the other hand, the aggregate profits of self-employed workers are given by the earnings from the production of the informal good minus their salary, that is:

$$\Pi_t^S = P_t^S Q_t^S - W_t^S \mu_t L_t^S, \tag{2.25}$$

countries with high rates of informality (see for example Çiçek & Elgin (2011))

Therefore, the aggregate of profits is given by the sum of profits of the producers in the formal sector, profits of the producers in the informal sector, and profits of the producers of the final good, as follows:

$$\Pi_t = \Pi_t^F + \Pi_t^S + (1 - MC_t) Y_t, \tag{2.26}$$

The one-period bond market clears in a way that satisfies the working capital requirements of formal firms, that is:

$$B_{t+1} = \kappa W_t^F L_t^F, \tag{2.27}$$

Combining the representative household budget constraint (3), the government budget constraint (23), the aggregate benefits (27), and the one-period bond market clearing condition (28), we obtain the following market-clearing condition:

$$Y_t = C_t + G_t + I_t + \xi V_t^F. \tag{2.28}$$

2.4.7 Stochastic processes

We assume that both aggregate TFP and the formal sector TFP follow an AR(1) process as shown below:

$$A_t = \rho_A A_{t-1} + \varepsilon_{A,t}, A_t^F = \rho_A A_{t-1}^F + \varepsilon_{A^F,t}, \tag{2.29}$$

where $\rho_A \in (0, 1)$ denotes the persistence of aggregate productivity and formal sector productivity shocks. Furthermore, productivity shocks are independent and identical distributed random variables, that is $\varepsilon_{A,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma_A^2)$ and $\varepsilon_{A^F,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma_{A^F}^2\right)$.

The emergence of the virus V_t is assumed to follow an zero-mean $ARIMA(p, d, q)$ process that is formally written by the following expression:

$$\left(1 - \sum_{m=1}^{p} \rho_{v,m} \mathbb{L}^m\right) V_t = \left(1 + \sum_{n=1}^{q} \varrho_{v,n} \mathbb{L}^n\right) \varepsilon_{v,t}, \tag{2.30}$$

where $\mathbb{L}$ is the lag operator, $\{\rho_{v,m}\}_{m=1}^{p}$ are the parameters of the autoregressive part of the model, $\{\varrho_{v,n}\}_{n=1}^{q}$ are the parameters of the moving average part, and $\varepsilon_{v,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma_v^2\right)$ captures exogenous outbreaks of the virus.

Finally, we assume that the fraction of output that the government spends g_t follows an AR(1) process, that is:

$$g_t = \left(1 - \rho_g\right) g + \rho_g g_t + \varepsilon_{g,t}, \tag{2.31}$$

here $g \in (0, 1)$ denotes the average of government expenditures to GDP ratio, $\rho_g \in (0, 1)$ represents the government spending shocks persistence, where government spending shocks are independent and identical distributed random variables, that is $\varepsilon_{g,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma_g^2\right)$.

2.5 Calibration

This section details the calibration strategy for the model parameters. First, we mute the virus outbreaks by simulating a pre-pandemic scenario in which we seek to match moments in the Mexican economy. Then, once the model's structural parameters have been obtained, we transform some key parameters to adapt the model to a fortnightly frequency. Finally, we calibrate the parameters related to the pandemic block.

2.5.1 Pre-pandemic scenario

The base structure of our model in the pre-pandemic scenario is based on the Alberola & Urrutia 's (2020) model, with the difference that we use a CES production function instead of the Cobb-Douglas production technology. The main reason for this change is that the lockdown policy totally or partially restricts the use of labor so that in the case of a complete closure with the Cobb-Douglas function, the output becomes zero due to the lack of substitution between inputs. Therefore, considering this change in the production function, we recalibrate the model parameters.

Model parameters in the pre-pandemic scenario are categorized into three groups. The first group includes commonly used Real Business Cycle (RBC) and New Keynesian (NK) literature parameters. The second group comprises parameters typically used in the Mexican economic literature or specific to the Mexican economy. The final group of parameters is selected to replicate some target values of the model in steady-state and to match key business cycle moments for Mexico.

For the first block of parameters, we choose the discount factor, the inverse of the Frisch labor supply elasticity, the capital share in producing the final good, and the capital depreciation rate according to the standard business cycle literature. The elasticity of substitution between capital and labor, the elasticity of substitution between varieties, and the parameters associated with the Taylor rule correspond to the prototype New Keynesian model.

For the second block, we obtain parameters widely used in literature and those characteristics of the Mexican economy. The elasticity of substitution between formal and informal inputs is obtained from Restrepo-Echavarria (2014). A standard value in literature for the elasticity of the matching function is the one obtained by Blanchard & Diamond (1989), which we will use in our calibration. The government expenditures to GDP ratio is obtained from Alberola & Urrutia (2020), which calculates its empirical mean. We set the payroll tax's value following the estimates of Ordonez (2014). Leyva & Urrutia (2020) reported that, on average, a worker lasts 2.8 years in a formal job, so we set the quarterly separation rate consistent with this value. Finally, the requirement for working capital in the formal sector, which has no empirical counterpart, corresponds to the average of the total short-term credit to manufacturing GDP ratio calculated by Meza et al. (2019).

Finally, we calibrate labor disutility, informal sector productivity, search costs for the unemployed, workers' bargaining power, and the costs of posting vacancies to match Mexico's employment rate, informality rate, unemployment rate, formal sector wage premium, and hiring costs over the wage bill, respectively. While the standard deviation of TFP shocks, the persistence of productivity shocks, the strength of the wealth effect on labor supply, the standard deviation of formal TFP shocks, the fraction of firms that do not change prices, the standard deviation of demand shocks, the persistence of demand shocks, the capital adjustment costs, and the elasticity between formal and informal goods to match the Mexican economy's second moments, such as GDP volatility, the first autocorrelation of GDP, the relative volatility of employment to GDP, the volatility of the informality rate, the volatility of the inflation rate, the correlation between inflation and GDP, the relative volatility of consumption to GDP the relative volatility of investment to GDP, and the correlation between employment and GDP respectively. The moments of the Mexican economy are obtained from the calculations by Alberola & Urrutia (2020).

Table 2.3 shows this section's calibrated parameters, grouped by blocks divided by a thicker line. The table's first column shows each parameter's name, the symbol that represents it in the second column, and the parameter's value in the third column. The fourth column shows the literature source or target calibration. Finally, the theoretical and empirical moments are shown in Table 2.4. We note that the model replicates a countercyclical informality rate close to its empirical value.

2.5.2 Adjustment to a fortnightly frequency

Different works that use epidemiological models to simulate the dynamics of COVID-19 use high-frequency data (see Atkeson (2020); Busato et al. (2021); Eichenbaum et al. (2021, 2022), among others). The high-frequency data allows us to accumulate active cases of the disease since, following Atkeson (2020), when a person becomes ill with COVID-19, in 18 days, on average, they recover or die. Therefore, we adjust the parameters of our model to work on the biweekly frequency.

To adjust our model on a biweekly basis, we only need to adjust eight parameters: the discount factor β, the capital stock depreciation rate δ, the fraction of firms that do not change their prices

Table 2.3: Pre-pandemic structural parameters

Parameters	Value	Source / Target
β, discount factor	0.990	RBC literature
ϕ, inverse of Frisch labor supply elasticity	1.000	
α, capital share in production function	0.333	
δ, capital depreciation rate	0.025	
ν, elasticity of substitution between capital and labor	0.500	NK literature
η, elasticity of substitution between varieties	5.000	
$\varphi_{i,\pi}$, inflation feedback in Taylor rule	1.500	
$\varphi_{i,y}$, output gap feedback in Taylor rule	0.250	
ϵ, elasticity of substitution formal/informal	5.000	Restrepo-Echavarria (2014)
φ, elasticity of matching function	0.400	Blanchard & Diamond (1989)
g, average government expenditures to GDP ratio	0.090	Alberola & Urrutia (2020)
τ, payroll tax	0.250	Ordonez (2014)
s, separation rate (formal turnover)	0.088	Leyva & Urrutia (2020)
κ, working capital requirement formal sector	0.210	Meza et al. (2019)
ψ, labor disutility	1.806	Employment rate: 55.7%
χ, informal sector productivity	0.662	Informality rate: 55.8%
ς, search cost for unemployed	52.509	Unemployment rate: 4.75%
γ, workers' bargaining power	0.754	Formal wage premium: 13.0%
ξ, cost of posting a vacancy	0.383	Hiring costs over wage bill: 3.4%
σ_A, standard deviation of aggregate TFP shocks	0.346	Volatility of GDP: 1.57%
ρ_A, persistence of TFP shocks	0.906	First autocorrelation of GDP: 0.92
ω, strength of wealth effect in labor supply	0.026	Relative volatility employment: 0.42
σ_{A^F}, standard deviation of formal TFP shocks	0.435	Relative volatility informality: 0.53
θ, fraction of firms not changing prices	0.550	Volatility inflation: 0.48
σ_g, standard deviation of demand shocks	0.688	Correlation inflation, GDP: -0.35
ρ_g, persistence of demand shocks	0.736	Relative volatility consumption: 1.11
ϑ, capital adjustment costs	20.996	Relative volatility investment: 1.98

Source: Own elaboration.

Table 2.4: Theoretical and empirical moments

Moment	Symbol	Data Mexico	Pre-pandemic scenario
Volatility: output	$\sigma\left(Y_t\right)$	1.57	1.57
First autocorrelation: output	$\rho\left(Y_t, Y_{t-1}\right)$	0.92	0.92
Volatility: inflation	$\sigma\left(\pi_t\right)$	0.48	0.48
Correlation: inflation and output	$\rho\left(\pi_t, Y_t\right)$	-0.35	-0.35
Relative volatility: employment	$\sigma\left(L_t\right)/\sigma\left(Y_t\right)$	0.42	0.42
Correlation: employment and output	$\rho\left(L_t, Y_t\right)$	**0.76**	**0.79**
Relative volatility: informality rate	$\sigma\left(l_t^S\right)/\sigma\left(Y_t\right)$	0.53	0.53
Correlation: informality rate output	$\rho\left(l_t^S, Y_t\right)$	**-0.56**	**-0.48**
Relative volatility: consumption	$\sigma\left(C_t\right)/\sigma\left(Y_t\right)$	1.11	1.11
Relative volatility investment	$\sigma\left(I_t\right)/\sigma\left(Y_t\right)$	1.98	1.98

Source: Own elaboration.
Note: The empirical moments were obtained from Alberola & Urrutia (2020).

θ, the formal sector working capital requirement κ, the capital adjustment costs ϑ, the separation rate of the formal sector s, the Taylor rule coefficient associated with the output gap $\varphi_{i,Y}$ and the costs of posting a vacancy ξ. The adjustment of the parameters to biweekly frequency is detailed below.

We choose the discount factor so that the quarterly real interest rate is 1%, equivalent to a biweekly real interest rate of 0.17%; therefore, we adjust the discount factor as the biweekly gross interest rate inverse. The capital depreciation rate is assumed to depreciate at a quarterly rate of 2.5%, which implies that capital depreciates 0.42% every fortnight. In our calibration, we obtained that firms reset their prices every 2.1 quarters, equivalent to 12.6 fortnights; therefore, 92.1% of the firms do not change their prices. The formal sector working capital requirement is set so that the quarterly average empirical ratio between total short-term credit and manufacturing GDP is 21%. Since total short-term credit is a stock variable and manufacturing GDP is a flow variable, their relationship does not hold over different periods. Therefore, when multiplied by six, the parameter that measures the quarterly formal sector working capital requirement is equivalent to the biweekly formal sector working capital requirement. Similarly, the parameter that captures the capital adjustment costs is divided by six. The separation rate is set so that a worker lasts 2.8 years on average in a formal job, equivalent to 16.8 fortnights. Therefore, the biweekly separation rate is one-sixth of the quarterly separation rate. A standard value for the coefficient that measures the reaction of the interest rate to the output gap in the Taylor rule is 0.25; this value is divided by six to adjust to the biweekly frequency. Finally, the costs of posting vacancies are multiplied by six to adjust them to biweekly frequency. The parameters adjusted to the fortnightly basis are shown in the first block of Table 2.7.

2.5.3 Pandemic block parameter calibration

In this subsection, we calibrate the parameters associated with the pandemic block. For this purpose, we use new COVID-19 daily cases and new COVID-19 daily deaths from the CONACyT database. Subsequently, we aggregate the data on a fortnightly basis. The analysis period covers the second half of February 2020 to the second half of June 2022.

The pandemic block's parameters to be calibrated are the sensitivity of household utility to new cases of the disease, the average mortality rate, the recovery rate, the weight of consumption in the spread of the epidemic, the weight of labor in the spread of the epidemic, the weight of non-economic activity in the spread of the epidemic, the intensity of the lockdown policy concerning active cases, the persistence of the lockdown policy, and the parameters related to the $ARIMA(p, d, q)$ virus process.

We begin by obtaining the mortality rate mean in the period analyzed. For this purpose, we calculated the ratio between the biweekly series of COVID-19 deaths and the biweekly series of new COVID-19 cases. Following Atkeson (2020), the disease of COVID-19 lasts an average of 18 days. During this time, the infected person recovers or dies. Therefore, the total elimination rate of the virus on a fortnightly basis is set at 15/18. The recovery rate is obtained by subtracting the mortality rate mean from the total elimination rate.

The parameters that measure the weighting of consumption, employment, and non-economic activity in the spread of the virus are calibrated following Eichenbaum et al. (2021), where it is mentioned that the transmissions related to consumption and employment are around 1/6 of the

Table 2.5: Augmented Dickey-Fuller test

Variable	t-statistics	Critical value at 5%
$\log(V_t)$	0.003	-1.950
$\Delta\log(V_t)$	-4.414	-1.950

Source: Own elaboration.

Table 2.6: AIC and BIC values

Model	AIC criteria	BIC criteria
$ARMA(0,1)$	99.25	117.08
$ARMA(0,2)$	92.42	116.19
$ARMA(1,0)$	91.10	108.94
$ARMA(2,0)$	86.93	110.70
$ARMA(2,1)$	86.39	116.11
$ARMA(1,1)$*	84.41*	108.18*

Source: Own elaboration.

total time each. Hence, the transmissions related to the non-economic activity are the remaining 2/3 of the time. Therefore, the following 2×2 system is solved:

$$\frac{\varpi_c C_{ss}}{\varpi_c C_{ss} + \varpi_l \mu_{ss} L_{ss} + \varpi_o} = \frac{1}{6},$$

$$\frac{\varpi_l \mu_{ss} L_{ss}}{\varpi_c C_{ss} + \varpi_l \mu_{ss} L_{ss} + \varpi_o} = \frac{1}{6}.$$

Next, we estimate the parameters of the $ARIMA(p,d,q)$ virus process. For this purpose, we use data on new daily COVID-19 cases obtained from the CONACyT database and aggregate them fortnightly. Subsequently, we obtain the logarithm of the series and determine the order of integration of the process. To do this, we apply the augmented Dickey-Fuller test. Table 2.5 shows the results of this test. In the first row, we can see that the series in logarithms has at least one unit root. In the second row, we show the test results for the series in the first differences, where the test statistically rejects the existence of unit roots; this implies that the process is first-order integrated. Once we identify the order of integration of the process, we estimate the $ARMA(p,q)$ process on the series in the first differences using the lowest Akaike and Bayesian

Table 2.7: Parameters adjusted to biweekly model and pandemic block parameters

Parameter	Value	Quarterly target
β, discount factor	0.998	Real interest rate 1%
δ, capital depreciation rate	0.004	Capital depreciation rate 2.5%
θ, fraction of firms not changing prices	0.921	Firms reset prices every 2.1
κ, formal working capital requirement	1.260	Short-term credit to GDP: 21%
ϑ, capital adjustment costs	3.499	Capital adjustment costs: 20.996
s, formal separation rate	0.015	Avg. Duration in formality: 11.2
$\varphi_{i,y}$, output gap feedback in Taylor rule	0.004	Output gap Taylor rule: 0.250
ξ, costs of posting a vacancy	2.298	Posting vacancy costs: 0.383
φ_h, household sensitivity to new cases	0.250	Inflation rate (YoY) dynamics.
m, mortality rate	0.063	Average mortality rate: 6.3%
r, recovery rate	0.770	Disease duration 18 days
ϖ_c, consumption weight in virus propagation	0.240	Transmission by consumption: 1/6
ϖ_l, labor weight in virus propagation	0.300	Transmission by labor: 1/6
ϖ_o, non-economic weight in virus propagation	0.667	Transmission by non-economic: 2/3
ρ_v, pandemic shock $AR(1)$ coefficient	0.743	Estimation $ARMA(1,1)$ process
ϱ_v, pandemic shock $MA(1)$ coefficient	0.519	Estimation $ARMA(1,1)$ process
σ_v, standard deviation of pandemic shock	0.222	Estimation $ARMA(1,1)$ process
ρ_μ, lockdown policy persistence	0.800	GDP persistence
$\varphi_{\mu,s}$, lockdown elasticity to active cases	0.500	Minimum GDP (YoY): -21.9%

Source: Own elaboration.

information criteria to determine the best model. Table 2.6 shows the outputs of the model's Akaike and Bayesian information criteria, where the lowest values for the Akaike and Bayesian information criteria correspond to the $ARMA(1,1)$ model.

Once we have the parameters associated with the autoregressive process of the virus, we proceed to carry out simulations with different values of trial and error in the parameters related to the confinement policy and the sensitivity of household utility to new cases of the disease to replicate the dynamics of the pandemic in Mexico. First, we obtain the GDP, the population aged 15 and over, and the CPI from the INEGI database. Using this information, we construct the annualized growth rate of GDP per capita and the inflation rate, both demeaned by the average from 2019/Q1 to 2020/Q1. Subsequently, we carry out simulations varying the parameters related to the confinement policy. Finally, we compare our model's GDP and inflation behavior with the data. For this, we aggregate the artificial biweekly GDP and the annualized inflation rate data from our model at a quarterly frequency using the following expressions[3], respectively:

$$Y_t^Q = \frac{1}{6}\left[Y_t + \sum_{i=1}^{5} \frac{Y_{t-i}}{\prod_{j=0}^{i-1}(1+\pi_{t-j})}\right].$$

$$\pi_t^{Q,Ann} = \frac{1}{6}\sum_{i=0}^{5} \pi_{t-i}^{Ann}, 1+\pi_t^{Ann} = \prod_{j=0}^{23}(1+\pi_{t-j}).$$

Finally, we calibrate household sensitivity to new disease cases to replicate the observed dynamics of the inflation rate during the pandemic period. This is a key parameter in this process since it influences the curvature of inflation. Inflation is contained at the time of the pandemic outbreak; as economic restrictions are released, a gradual increase occurs (see Figure 2.3). Therefore, a higher parameter value cause consumption to be reduced more than output, so inflation will be contained at the beginning of the pandemic shock. The details of pandemic block parameters are shown in the second block of Table 2.7.

2.6 Results

In this section, we show the model's results and the performance to mimic the cyclical movements during the pandemic. Finally, we perform a counterfactual, removing informal employment from the model and comparing the dynamics of the output growth rate, the employment rate, and the inflation rate with the full model.

2.6.1 Impulse-response analysis

First, we induce the economy to face a pandemic shock, estimate the dynamics of the variables related to the pandemic and the macroeconomic variables of interest, and describe the behavior of the impulse-response functions (IRFs). Subsequently, we aggregate the data at a quarterly frequency and compare the variables of economic growth, employment rate, inflation rate, and

[3] The superscript Q indicates the variables in quarterly frequency, while the superscript Ann indicates the annualized variables.

informality rate with the data from Mexico to assess the model's ability to mimic the dynamics of these variables in the face of the pandemic shock.

Pandemic shock. In Figure 2.2, we show the IRFs of inducing a shock of size equal to the estimated variance of the virus's $ARMA(1,1)$ process. Panel (a) shows the spread of new infections, which increases up to 48.3% compared to the initial infected population. With the increase in the number of active cases of the disease, the government deployed a lockdown policy restricting employed personnel use by 63.7% of total employment (see panel (c)), causing some workers to be quarantined.

Both the forced quarantine and the decreased desire to work due to the risk of contagion led to sharp reductions in the employment rate by 17.9 points of its average, as shown in panel (n); however, the impact across sectors is different. On the one hand, in panels (d) and (e), we can see that informal employment is more affected than formal employment since informal employment saw a contraction of 76.3%, while formal employment only contracted 4.1%; this wide difference leads to a procyclical informality rate. On the other hand, informal employment recovers faster since it approaches its steady-state value around ten fortnights, while formal employment takes more than twenty fortnights to recover.

In our model, the lockdown policy indiscriminately restricts employment use in both sectors. However, given the frictions in the formal sector, most of the response to the pandemic shock is driven by the informal sector. At the same time, this feature allows the informal sector to recover faster since there are no entry costs.

Real wages in the formal sector experience steeper declines than in the informal sector. This disparity stems from the differing levels of flexibility within each sector. The informal sector's inherent flexibility increases labor demand, preserving workers' bargaining power. Conversely, the formal sector's rigidity leads to sharper reductions in labor demand, weakening workers' positions and translating into deeper salary cuts.

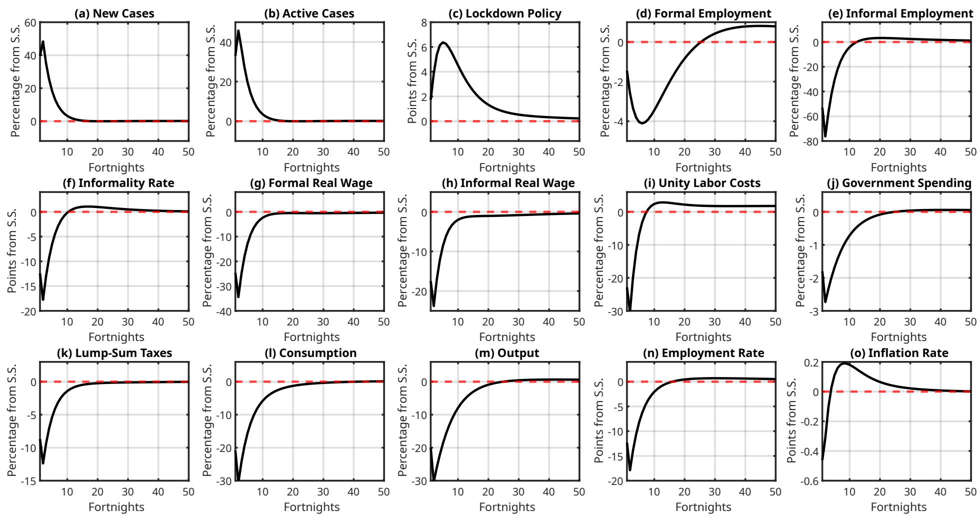
Government spending is linked to output, so the dynamics between them are proportional (see panels (j) and (m)). Lump-sum taxes are reduced to alleviate the economy and maintain household consumption patterns as much as possible. However, the informal sector makes government spending more dependent on lump-sum taxes since it does not pay payroll taxes, making the government's fiscal policies to alleviate consumption difficult. This is discussed further in subsection 2.6.2.

Both formal and informal employment contribute strongly to production. Hence, the sharp reduction in personnel in both sectors produced by the harsh confinement policy to contain the virus and the reduction in household labor supply leads to biweekly GDP contracting up to 30.4%, as shown in panel (j). Furthermore, in panel (l), we can see that the inflation rate falls about 0.46 points below the inflation target in the face of the pandemic; however, it rises rapidly and remains very persistently above the objective for more than 30 fortnights.

The fear of becoming infected through consumer activities causes households to reduce consumption by 0.86 percentage points more than output (see panels (l) and (m)), dropping an initial inflation rate as Eichenbaum et al. (2022). Meanwhile, in the recovery period, wage increases outpace job growth due to frictions in the formal sector; this has a two-fold impact on the inflation rate: on the one hand, it raises firms' costs faster than output, pushing unit labor costs upwards and fueling inflation (see panel (i)). On the other hand, it boosts government payroll tax collection, allowing for a quicker reduction in lump-sum taxes that tend to stimulate consumption (see panel (k)). As a result, consumption rebounds faster than production, causing inflationary pressures. On the other hand, in the Eichenbaum et al. (2022)'s model, the labor market lacks frictions and no government entity, which explains the differences in inflation dynamics.

Model vs. Data Now, we analyze the model's performance in replicating the data of our interest during the first two years of the pandemic. For this purpose, we work with the demeaned series for the annual GDP growth rate, the annual inflation rate, the employment rate, and the

Figure 2.2: Impulse-response to a pandemic shock



informality rate[4] to compare with the model's variables in response to a pandemic shock.

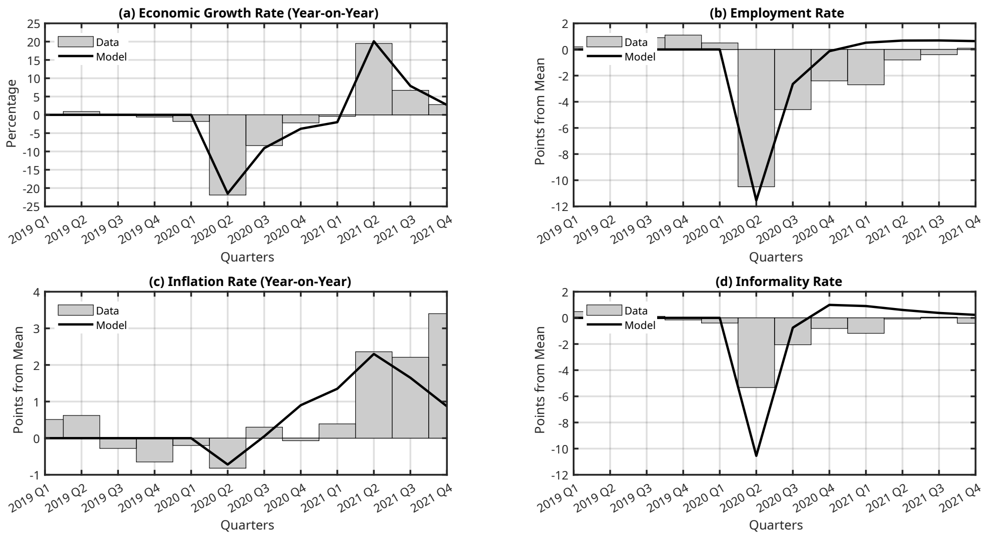
In Figure 2.3, we show the data compared to the model's IRFs aggregated quarterly. We induce a shock of the size equal to the variance of the estimated process of the virus, and then we match the initial period of the shock with the second quarter of 2020. In each panel, the bars represent the demeaned data corresponding to each variable, while the solid lines represent the model's IRFs to the pandemic shock.

It is not surprising that GDP adjusted well, at least in the first two quarters after the shock, since the parameters that govern the behavior of the lockdown policy were adjusted to replicate the size of the fall and persistence of GDP during the pandemic, however for the rest of variables the model fit the data well, our model reacts with similar dynamics and magnitudes. The main details to note between the model and the data are that the employment rate in our model is less persistent, the informality rate falls more and less persistent than in the data, and the inflation rate falls harder at the start of the pandemic shock.

More accurate results could be obtained by relaxing the assumption that the informal sector is

[4]The employment rate is constructed as the ratio of the employed population and the population aged 15 and over. The employed population, the population aged 15 and over, and the informality rate are obtained from the INEGI database.

Figure 2.3: Model vs. Data



composed entirely of self-employed workers since this assumption allows individuals to move freely between inactivity and the informal sector. Furthermore, by adding the search for a job and matching environment to the informal sector, informal employment would not be as volatile as shown in the IRFs. Furthermore, the appearance of new variants of the virus, the resilience of economic agents and the labor market in the face of the pandemic, mass vaccination, the disruption in the global supply chain, and the effects of the rest of the world on the domestic economy, among other things, cause differences with our simulations.

2.6.2 The role of informal employment

In this section, we assess the role of the informal sector in the main macroeconomic aggregates in the face of a pandemic shock. For this purpose, we perform a counterfactual exercise comparing the IRFs of the GDP growth rate, the employment rate, and the inflation rate, considering two cases. The first is the benchmark model; in this case, the labor market comprises formal and informal sectors. In the second case, employment is completely formal. We eliminated all informal sector variables from the benchmark model to achieve this. At the same time, the rest of the parameters remain unchanged.

Figure 2.4: Counterfactual excercise

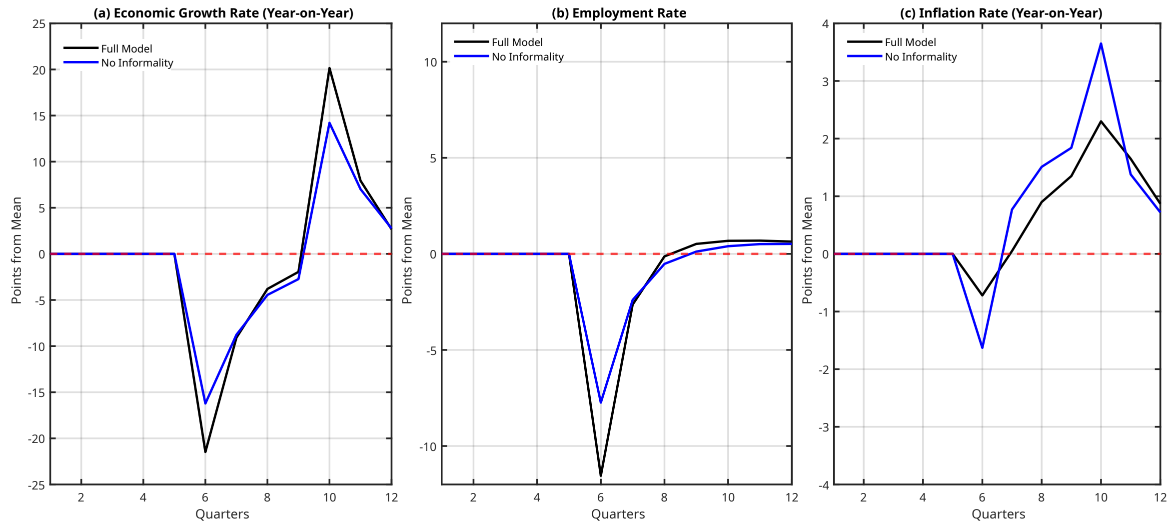


Figure 2.4 shows the dynamics of this comparison. The black line of each panel in the graph represents the IRFs to the pandemic shock of the full model. In contrast, the blue line is the IRFs to the pandemic shock of the model without informality. We note that GDP falls by about 5 pp less in the model without informality than in the full model. The main reason is that total employment in the model without informality contracted less than in the model with mixed employment, specifically 3.8 pp less. As we can see in Figure 2.2, formal employment is less affected by the pandemic shock than formal employment, but it takes longer to recover. Therefore, in the model without informality, total employment has the same characteristics as the formal sector.

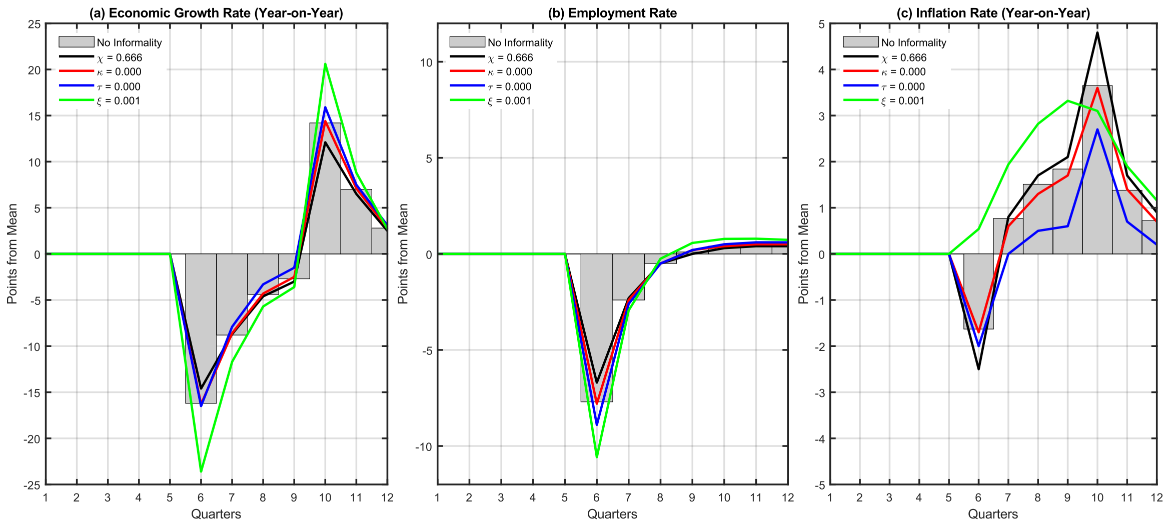
One of the most striking differences between the two models is the inflation rate IRF. The full model's inflation rate fluctuates between -0.7 pp and 2.3 pp. However, in the model without informality, the inflation rate is more volatile, ranging from -1.6 to 3.5 pp. This stark contrast underscores the significant impact of the informal sector on the pandemic crisis. It exacerbates the effects on economic growth and employment rates while mitigating inflationary pressures. To understand the underlying reasons for these differences, we conducted a sensitivity analysis of the parameters that differentiate the formal and informal sectors.

In our model, the informal sector is characterized by low productivity, limited access to working capital, tax evasion, and no entry costs. To ensure the robustness of our findings, we allow the formal sector to resemble the informal sector by gradually acquiring these characteristics and comparing the effects with the benchmark model. We meticulously vary the parameters associated with the characteristics that distinguish the formal sector from the informal sector, setting the values of these parameters to zero, except for the parameter associated with productivity. This rigorous approach allows us to identify the specific characteristics of the informal sector that drive the results observed in the face of the pandemic shock.

Figure 2.5 shows the IRF to the pandemic shock in the model without informality, varying the parameters that characterize the formal sector, resembling it to the informal sector characteristics. In each panel, the bars represent the model without informality, with the parameters unchanged. At the same time, the lines represent the modifications of this model by varying each of the parameters. For example, the black IRFs represent the model without informality with $\chi = 0.666$ when the formal sector is less productive. In this case, there is no significant difference in the dynamics of GDP growth and employment rates concerning the model without informality. However, the inflation rate is the most volatile. The main reason is that producing the same amount of formal goods is more expensive, producing inflationary pressures when the output behaves similarly to a more productive economy.

The red lines represent the IRFs of the model without informality when access to working capital is limited, that is when $\kappa = 0.000$. The IRFs colored in blue represent the case when the formal sector is exempt from taxes. Again, as in the previous case, there is no significant difference in the GDP and employment growth rate dynamics. However, in this case, there is less inflation. First, it is assumed that the spending behavior is procyclical. Hence, decreases follow falls in GDP in government purchases, which has a greater impact on aggregate demand, resulting in lower inflation. Second, when the payroll tax is zero, public spending is financed solely with lump-sum taxes. Finally, lump-sum taxes to finance government expenditures increase

Figure 2.5: Parameter sensitivity



significantly when the economy enters recovery, reducing inflationary pressures.

Finally, the green IRFs represent the case when there are no entry costs in the formal sector; this is the most similar case to when there is mixed employment since the GDP and the employment rate contract to a greater extent while the behavior of the inflation rate softens. First, near-zero entry costs provide greater labor market flexibility, allowing households to be employed or unemployed quickly. Therefore, in the face of forced quarantine, workers leave their work more easily, further reducing the employment rate. Given the above, there are further falls in GDP. However, this flexibility allows workers to be reinstated quickly, making the pandemic shock to the employment rate less persistent. At the same time, labor market flexibility allows firms to expand output without increasing wages, buffering inflation.

In summary, the two key features of the informal sector, tax exemption and low entry costs, significantly impact economic aggregates during a pandemic shock. In a scenario with negligible entry costs for formal businesses, the initial job losses due to a pandemic would be more severe, leading to a sharper decline in output. However, during recovery, low entry costs allow workers to swiftly re-enter the formal job market, facilitating a faster economic rebound.

In the scenario where the formal sector adopts a zero-payroll tax policy, like the informal sector, government revenue relies solely on lump-sum taxes. This reduces the impact on inflation compared to a scenario with payroll taxes. This difference arises because, as in the model without informality, employment contracts less than output (see Figure 2.4), causes payroll tax revenue to be reduced in a smaller proportion than output and to follow the government spending rule, it must reduce lump-sum taxes more strongly. By sharply reducing lump-sum taxes, the representative household will have greater disposable income, smoothing the effect on consumption and generating inflationary pressures. On the contrary, when government revenue depends exclusively on lump-sum taxes, these fluctuate along with output and are not reduced as much as in the previous case, which prevents greater consumption in an economy hit by confinement policies, which cushions the inflationary effect.

2.6.3 A note on welfare

In this section, we compare the households' welfare in the full model against the model without informality in the face of the pandemic shock. The households' welfare loss is greater in the model with mixed employment. The difference between the maximum welfare loss between the two cases is 6 pp, favoring the case of the economy without informal employment. However, the rapid recovery of informal employment makes it possible to reduce the gap in the loss of well-being during the two years of the pandemic. However, the economy is still 0.6 pp lower without informal employment. The above results imply that the representative household would prefer to live in an economy without informal employment during the pandemic shock. That is, they prefer a lower loss of output and employment at the cost of higher price increases.

Our results support the arguments of Loayza (2020), which state that the informal economy makes economies more vulnerable to the COVID-19 crisis. Furthermore, it is consistent with the results obtained by Alberola & Urrutia (2020), who submit a similar model to different shocks that perturb the economy, where households prefer that informality is absent. Therefore, it is worth paying attention to policies that reduce informal activity in emerging and developing countries to prevent technological, demand, monetary, financial, and pandemic shocks from causing further economic losses.

2.7 Conclusion

The COVID-19 health crisis caused the greatest economic damage in the last 60 years. However, the effects between the regions were differentiated. Economic growth and employment affected Latin America and the Caribbean region most; however, other regions suffered greater price changes. In addition, the LAC region is characterized by large informal sectors, so studying the role of the informal sector during the pandemic is of utmost importance to understand the impact of the crisis in this region.

In this paper, we have presented a DSGE model with labor market frictions and pandemic dynamics simulating the behavior of the COVID-19 crisis to analyze the role of the informal sector during the pandemic. We characterize the informal sector as a sector that does not face entry costs, does not pay taxes, is excluded from the credit market, and is less productive than the formal sector. On the other hand, we include a detailed pandemic block with a stochastic emergence of the virus that spreads through economic activities such as consumption and labor and non-economic activities, producing new cases. When new cases accumulate, they generate active cases, while others recover or die. As a result, the government imposes a lockdown policy restricting the use of labor in both sectors to prevent further spread and mortality. In addition, as disease cases increase, households decrease their desire to consume and to be employed to reduce the risk of contagion.

We first calibrate the model for Mexico's economy as a potential representative of the informal economy in the Latin American and Caribbean region. Our simulations show that employment is falling in both sectors, although the dynamics differ. On the one hand, the restrictions due to the pandemic shock significantly reduce informal employment more than formal employment. This prevents households from making up for formal job losses by becoming informal employees, producing a procyclical informality rate. On the other hand, the impact on formal employment is more persistent, so informal employment recovers more quickly, given the high flexibility of the informal sector. As a result, job losses due to confinement produce a sharp drop in output. In addition, households' repressed desire for consumption at the beginning of the pandemic produced reductions in aggregate demand that caused the inflation rate to fall. However, in the recovery phase, the persistence of the lockdown policy means that the aggregate supply does not recover at the rate of the aggregate demand, leading to strong price increases.

Subsequently, to assess the role of the informal sector in the COVID-19 health crisis, we carry out a counterfactual exercise eliminating informal employment from the economy, paying special attention to the economic growth rate, the employment rate, and the inflation rate. Finally, we modify the model's characteristics without informality one by one to resemble the informal sector. We find that the presence of the informal sector aggravates the damage to output and employment but cushions the inflationary pressures derived from the crisis. The channel through which the informal sector operates in causing the effects on economic growth, employment, and inflation mentioned above is due to its low entry costs, i.e., high flexibility, and that it is payroll tax-free. The high flexibility allows for greater employment outflows at the time of impact and greater inflows in the recovery phase. As a result, the strong job losses driven by the confinement policy cause greater contractions in GDP. On the other hand, the informal sector's ability to evade taxes means that the government has less room to alleviate the economy, so it does not reduce lump-sum taxes as much as when informality is absent. This further reduces households' disposable income, which prevents them from smoothing their consumption and, therefore, generates a buffer effect on inflation.

Lastly, we compare the welfare loss of the model with mixed employment and the model without informal employment in the face of the pandemic shock. We find that the greatest welfare loss occurs where there is informality, which implies that the representative household prefers to face the pandemic shock when there is no informal employment.

In this sense, public policies must adopt a focused approach to promote formal employment in Latin American and Caribbean countries. This approach mainly aims to reduce the prevalence of labor informality, which will help mitigate the negative impacts on GDP and employment during upcoming crises like the one we recently faced due to the COVID-19 pandemic. At the same time, this strategy will ensure workers and households a safer work environment backed by safeguards and protections.

Our results partly explain the differentiated effects of the crisis in terms of the main macroeconomic aggregates. However, the model can be improved if some extensions are considered. First, consider the effects of the rest of the world on the global supply chain in a two-country environment. Secondly, the confinement policy was directed towards non-essential economic sectors, mainly in the service sector, so the high economic dependence of this sector is important for the analysis. Finally, consider the risk perception with vaccination since households may feel safer and increase demand with a repressed supply, causing strong inflationary pressures.

Chapter 3

Nowcasting Mexico’s Monthly Industrial Production Index

3.1 Introduction

In the intricate landscape of economic analysis, investors and policymakers often refer to macroeconomic indicators such as national accounts, labor market surveys, and price indexes to assess an economy's overall health, performance, and upcoming trends. These indicators are crucial in guiding investors to make informed decisions regarding capital allocation and assisting policymakers in formulating appropriate economic strategies.

However, the timely response of investors and policymakers to emerging economic trends is often impeded by the delayed release of official macroeconomic indicators, creating a restricted timeframe for adaptation to real-time economic activity. The lag in data availability can hinder the swift adjustment needed in response to dynamic market conditions. In addition, this delay in data availability can curtail the expeditiousness with which policymakers can adapt to dynamic market conditions; this is particularly crucial during recessions, as noted by Nissilä (2020), where timely decision-making can have profound implications for a nation's macroeconomic and financial stability.

There is a growing imperative to integrate other timely economic indicators into the analytical framework, recognizing the inherent limitations of relying solely on traditional indicators with delayed releases. These timely indicators play a pivotal role in employing nowcasting techniques, enabling the updating of lagging indicators through informed estimates. By doing so, stakeholders can mitigate the constraints imposed by delayed macroeconomic data, fostering a more adaptive and responsive approach to navigating the ever-evolving economic landscape.

In Mexico, in light of this concern, the National Institute of Statistics and Geography (INEGI in Spanish) has undertaken an initiative to develop nowcasts that provide estimates of the economic activity indicators, including the Gross Domestic Product, the private consumption, the Global Indicator of Economic Activity, and the Indicator of Manufacturing Activity. These initiatives are referred to as "Estimación Oportuna del PIB Trimestral" (EOPIBT), "Indicador Mensual del Consumo Privado del Mercado Interior" (IMCPMI), "Indicador Oportuno de la Actividad Economica" (IOAE), and "Indicador Mensual Oportuno de la Actividad Manufacturera" (IMOAM), respectively. They incorporate more timely economic, financial, and non-traditional indicators such as economic and labor surveys, interest rates, exchange rates, stock market indexes, and Google search indexes.

The Industrial Production Index or Monthly Industrial Activity Index (IMAI, in Spanish) emerges as a significant nowcasting indicator for the Global Index of Economic Activity (IGAE, in Spanish), according to the findings of Corona et al. (2021). Simultaneously, the IGAE is a relevant indicator for GDP nowcasting, as Gálvez-Soriano (2020) highlighted. While IMAI is more timely than its counterparts, its information is presented with a one-month delay, potentially biasing IGAE and GDP estimates for the most recent month.

This paper aims to identify the most relevant IMAI predictors and use them in a model for nowcasting IMAI one step ahead in the January 2018 - December 2023 analysis period. Our lack of previous information about the relevant indicators for estimating IMAI forces us to propose several. Therefore, we propose a large dataset of potential predictors encompassing timely economic, financial, survey-based, and non-traditional indicators. On the other hand, it is widely recognized that employing a large data set does not necessarily guarantee more accurate predictions; we use variable section methods to filter out irrelevant variables and refine the set of potential predictors.

Once we have created sets of covariates selected by the variable selection methods, we construct a common factor for each using a dynamic factor model (DFM). Finally, we trained a linear model with ARMA errors for each common factor. We tested the performance of the different models using the mean absolute error (MAE) as an accuracy metric compared to a naive ARIMA model.

We found that since the COVID-19 pandemic, non-traditional indicators have become relevant in the variable selection models, which allows us to manage the uncertainty of the models when generating the nowcasts. The models that show the best and equal performance are LASSO and

Elastic Net, outperforming the dynamic factor models. Although the performance of the models is similar, the LASSO model follows the principle of parsimony by selecting a smaller number of predictors and is less expensive in terms of computational complexity than the Elastic Net method.

The paper follows this structure: Section 3.2 provides a comprehensive overview of the indicators utilized in the nowcasting exercise, detailing their sources and availability. Section 3.3 delves into the methodology, elucidating the variable selection models and the dynamic factors model. Section 3.4 meticulously outlines the IMAI nowcasting exercise, commencing with a description of the data treatment, followed by the training and selection of hyperparameters for the variable selection models, the construction of dynamic factors, and ultimately, the establishment of the linear model with autoregressive errors for IMAI nowcasting. Section 3.5 presents the findings, while Section 6 offers concluding remarks.

3.2 Data and sources

3.2.1 Traditional indicators

For our analysis, we collect a large set of macroeconomic indicators that have been used to nowcasting the economic activity in Mexico on the condition that they are more timely than the IMAI (see, for example, Corona et al. (2017); Caruso (2018); Gálvez-Soriano (2020); Corona et al. (2021)). In addition, we explore other timely indicators related to economic activity and the industrial sector, such as stock market indexes by sector, political economy indicators, consumer confidence indexes, and business confidence indexes, among others.

Seventy-seven traditional macroeconomic indicators classified into economic, financial, and survey-based were collected from January 2003 to December 2023. Most of the variables were obtained from their source already adjusted for seasonality, for those that are not, we seasonal adjust them using X-13ARIMA-SEATS. Table 3.1 provides a detailed breakdown of these traditional macroeconomic variables' classification, source, and timespan. Later, we discuss how we transform each potential predictor and deal with the "ragged edges" problem.

Table 3.1: Traditional indicators

Indicator	Source	Timespan
Panel A. Economic Indicators		
Consumer Price Index: Total	INEGI	01/2003-12/2023
Consumer Price Index: Core	INEGI	01/2003-12/2023
Economic Policy Uncertainty Index	EPUI	01/2003-12/2023
Employees: Mexican Social Security Institute	IMSS	01/2003-12/2023
Industrial Production Index: USA	FRED	01/2003-12/2023
Manufacturing Production Index: USA	FRED	01/2003-12/2023
Producer Price Index: Total	INEGI	12/2003-12/2023
Producer Price Index: Excluding Oil	INEGI	12/2003-12/2023
Producer Price Index: Secondary Activities	INEGI	01/2003-12/2023
Producer Price Index: Secondary Activities Excluding Oil	INEGI	01/2003-12/2023
Production: Cars	INEGI	01/2003-12/2023
Production: Trucks, Tractors, and Buses	INEGI	01/2003-12/2023
Sales: Cars	INEGI	01/2003-12/2023
Sales: Convenience and Department Stores	ANTAD	01/2003-12/2023
Sales: Trucks	INEGI	01/2003-12/2023
Unemployment Rate: USA	FRED	01/2003-12/2023
Panel B. Financial Indicators		
Amount Transacted: Cards	BANXICO	01/2009-12/2023
Amount Traded: Interbank Electronic Payment System	BANXICO	01/2009-12/2023
Cboe Volatility Index	INVESTING	01/2003-12/2003
Equilibrium 28-days Interbank Interest Rate	BANXICO	01/2003-12/2023
Fixed Exchange Rate	BANXICO	01/2003-12/2023
Price and Quote Index: Total	BANXICO	01/2004-12/2023

Price and Quote Index: Industrial	BANXICO	03/2009-12/2023
Price and Quote Index: Materials	BANXICO	03/2009-12/2023
Price and Quote Index: Financial Services	BANXICO	03/2009-12/2023
Price and Quote Index: Frequently Consumed Goods	BANXICO	03/2009-12/2023
Price and Quote Index: Health	BANXICO	03/2009-12/2023
Price and Quote Index: Services and Non-Basic Consumer Goods	BANXICO	03/2009-12/2023
Price and Quote Index: Telecommunications Services	BANXICO	03/2009-12/2023
Standard & Poor's 500	INVESTING	01/2003-12/2023
Panel C. Survey Indicators		
Aggregate Trend Index: Commerce	INEGI	06/2011-12/2023
Aggregate Trend Index: Construction	INEGI	06/2011-12/2023
Aggregate Trend Index: Manufacturing	INEGI	01/2004-12/2023
Aggregate Trend Index: Services	INEGI	01/2017-12/2023
Expected Real GDP by Private Sector Economics Specialists	BANXICO	01/2003-12/2023
Business Confidence Index: Commerce	INEGI	06/2011-12/2023
Business Confidence Index: Construction	INEGI	06/2011-12/2023
Business Confidence Index: Manufacturing	INEGI	01/2004-12/2023
Business Confidence Index: Services	INEGI	01/2017-12/2023
Commodity Inventory: Commerce	INEGI	06/2011-12/2023
Consignment and/or Commission Income: Commerce	INEGI	06/2011-12/2023
Consumer Confidence Index	INEGI	01/2003-12/2023
Delivery of Products: Manufacturing	IMEF	01/2005-12/2023
Delivery of Products: No Manufacturing	IMEF	01/2005-12/2023
Domestic Demand for Products: Manufacturing	INEGI	01/2004-12/2023
Domestic Demand for Services: Services	INEGI	01/2017-12/2023
Employment: Commerce	INEGI	06/2011-12/2023
Employment: Construction	INEGI	06/2011-12/2023
Employment: Manufacturing	IMEF	01/2005-12/2023
Employment: Manufacturing	INEGI	01/2004-12/2023

Employment: No Manufacturing	IMEF	01/2005-12/2023
Employment: Services	INEGI	01/2017-12/2023
Expenditures for Consumption of Goods and Services: Services	INEGI	01/2017-12/2023
Exports: Manufacturing	INEGI	01/2004-12/2023
Final Goods Inventories: Manufacturing	INEGI	01/2004-12/2023
Input Prices: Manufacturing	INEGI	01/2004-12/2023
Inventory: Manufacturing	IMEF	01/2005-12/2023
Investment in Plant and Equipment: Manufacturing	INEGI	01/2004-12/2023
Manufacturing Index	IMEF	01/2005-12/2023
Manufacturing Order Index	INEGI	01/2004-12/2023
Net Purchases: Commerce	INEGI	06/2011-12/2023
Net Sales: Commerce	INEGI	06/2011-12/2023
New Orders: Manufacturing	IMEF	01/2005-12/2023
New Orders: No Manufacturing	IMEF	01/2005-12/2023
No Manufacturing Index	IMEF	01/2005-12/2023
Plant Capacity Utilization: Manufacturing	INEGI	01/2004-12/2023
Production: Manufacturing	IMEF	01/2005-12/2023
Production: Manufacturing	INEGI	01/2004-12/2023
Production: No Manufacturing	IMEF	01/2005-12/2023
Revenues from the Rendering of Services: Services	INEGI	01/2017-12/2023
Right Time to Invest: Commerce	INEGI	06/2011-12/2023
Right Time to Invest: Construction	INEGI	06/2011-12/2023
Right Time to Invest: Manufacturing	INEGI	01/2004-12/2023
Right Time to Invest: Services	INEGI	01/2017-12/2023
Sales Prices: Manufacturing	INEGI	01/2004-12/2023
Total Contracts and Subcontracts: Construction	INEGI	06/2011-12/2023
Works Performed as Prime Contractor: Construction	INEGI	06/2011-12/2023
Works Performed as Subcontractor: Construction	INEGI	06/2011-12/2023

Source: Own elaboration.

3.2.2 Non-traditional indicators

Recent research has harnessed Google search indexes to reinforce the forecasting of macroeconomic indicators, as exemplified by studies such as Nagao et al. (2019), Bantis et al. (2023), and Kohns & Bhattacharjee (2023). Google Trends indexes provide real-time data on searches conducted on the Google website within specific timeframes and geographical locations. These indices reveal consumer behaviors regarding online shopping, job searches, solvency or loan applications, healthcare, natural disasters, political and economic interests, etc. Therefore, when timely hard indicators are absent, Google search indexes complement these.

In the context of Mexican macroeconomic indicators, Corona et al. (2021) uses a large set of Google Search Terms based on various phenomena particulars of the Mexican economy for the IGAE nowcasting, showing that terms related to the pandemic, such as "facemask" and "quarantine," improve the IGAE out-of-sample forecast in the pandemic period.

However, Kohns & Bhattacharjee (2023) opted not to incorporate Google Search Terms into their analysis due to concerns about capturing spurious behavior. For example, Corona et al. (2021) uses the Google Search Term 'Muertos' ('dead' in English), which exhibited seasonal patterns in November coinciding with Mexico's Day of the Dead celebration, which makes it difficult to isolate internet searches related to murders in Mexico. Other Search Terms considered by Corona et al. (2021) have homographs. For example, the Search Term 'Peso,' referring to the Mexican peso currency, has homographs in Spanish related to weight.

To avoid capturing spurious behaviors, we use Search Categories or Topics instead; therefore, we consider Google Search Topics Indexes that cover the Search Terms used in Corona et al. (2021), and we added some other topics that characterize the Mexican economy and could be relevant, such as drought and water scarcity, power outages, hurricanes, organized crime, wars against drug trafficking, among others. However, we left some Search Terms that we did not find any Google Search Topics and do not have homographs. In addition, we use the Google Search Categories and Topics taken into account by Kohns & Bhattacharjee (2023), which include general other economic search indexes that can work well in any economy.

Table 3.2 lists the Google Trends Categories, Topics, and Search Terms used as predictor candidates in our nowcasting model. Unlike traditional variables, Google's historical search index data is sensitive to searches in recent periods since according to Bantis et al. (2023), the index does not measure the number of search volumes for privacy reasons. Instead, it provides an index ranging from 0 to 100, where 0 indicates insufficient data for this query, and 100 indicates the maximum popularity of the search term, topic, or category. The index built and provided by Google does not have decimals, so some searches are not zero but are not greater than one either; for this, they are assigned "< 1". In addition, Google search indexes may exhibit deterministic trends and seasonal patterns. In Section 3.4, we show how we deal with all these issues.

Table 3.2: Non-traditional indicators

Google Trends Search Index	**Category or Query ID**	**Timespan**
Panel A. Categories		
Autos & Vehicles	Category: 47	01/2004-12/2023
Business News	Category: 784	01/2004-12/2023
Business Services	Category: 329	01/2004-12/2023
Construction, Consulting, & Contracting	Category: 652	01/2004-12/2023
Credit & Lending	Category: 279	01/2004-12/2023
Economy News	Category: 1164	01/2004-12/2023
Environmental Issues	Category: 82	01/2004-12/2023
Financial Markets	Category: 1163	01/2004-12/2023
Food & Drink	Category: 71	01/2004-12/2023
Grocery & Food Retailers	Category: 121	01/2004-12/2023
Health	Category: 45	01/2004-12/2023
Home & Garden	Category: 11	01/2004-12/2023

Hotels & Accommodations	Category: 179	01/2004-12/2023
Investing	Category: 107	01/2004-12/2023
Manufacturing	Category: 49	01/2004-12/2023
Politics	Category: 396	01/2004-12/2023
Sports	Category: 20	01/2004-12/2023
Transportation & Logistics	Category: 50	01/2004-12/2023
Travel	Category: 67	01/2004-12/2023
Vehicle Brands	Category: 815	01/2004-12/2023
Vehicle Licensing & Registration	Category: 170	01/2004-12/2023
Welfare & Unemployment	Category: 706	01/2004-12/2023
Panel B. Topics		
Affordable Housing	Query: %2Fm%2F09jvc1	01/2004-12/2023
Andres Manuel López Obrador	Query: %2Fm%2F035m7s	01/2004-12/2023
Bankruptcy	Query: %2Fm%2F01hhz	01/2004-12/2023
China	Query: %2Fm%2F0d05w3	01/2004-12/2023
Citizens' Movement	Query: %2Fg%2F15dp8rct	01/2004-12/2023
Conflict	Query: %2Fm%2F0n5w902	01/2004-12/2023
Coronavirus	Query: %2Fm%2F01cpyy	01/2004-12/2023
Corruption	Query: %2Fm%2F09pngm	01/2004-12/2023
Crisis	Query: %2Fm%2F02gyy_	01/2004-12/2023
Donald Trump	Query: %2Fm%2F0cqt90	01/2004-12/2023
Drought	Query: %2Fm%2F099lp	01/2004-12/2023
Drug Cartel	Query: %2Fm%2F03bwzg9	01/2004-12/2023
Earthquake	Query: %2Fm%2F02r97	01/2004-12/2023
Ecologist Green Party of Mexico	Query: %2Fm%2F028y37	01/2004-12/2023
Economic Crisis	Query: %2Fg%2F1211cg58	01/2004-12/2023
Election Contest	Query: %2Fm%2F02l3h	01/2004-12/2023
Enrique Peña Nieto	Query: %2Fm%2F07zcdm	01/2004-12/2023
Exchange Rate	Query: %2Fm%2F018m33	01/2004-12/2023

Felipe Calderón	Query: %2Fm%2F06bbbt	01/2004-12/2023
Foreclosure	Query: %2Fm%2F02tp2m	01/2004-12/2023
Gasoline	Query: %2Fm%2F05wy2	01/2004-12/2023
Health Crisis	Query: %2Fm%2F0h3p62w	01/2004-12/2023
Homicide	Query: %2Fm%2F0x2fg	01/2004-12/2023
House Price Index	Query: %2Fm%2F0gn3x3	01/2004-12/2023
Huachicolero	Query: %2Fg%2F11c7wh9d48	01/2004-12/2023
Human Migration	Query: %2Fg%2F121jc7sl	01/2004-12/2023
Hurricane	Query: %2Fg%2F1234z5fb	01/2004-12/2023
Inflation	Query: %2Fm%2F09jx2	01/2004-12/2023
Institutional Revolutionary Party	Query: %2Fm%2F0m4ms	01/2004-12/2023
Interest Rate	Query: %2Fm%2F04n7dpf	01/2004-12/2023
Investment	Query: %2Fm%2F0g_fl	01/2004-12/2023
Joaquín Guzmán	Query: %2Fm%2F0bn8n2	01/2004-12/2023
Job	Query: %2Fm%2F04115t2	01/2004-12/2023
Mexican Drug War	Query: %2Fm%2F0273lbz	01/2004-12/2023
Mexican Peso	Query: %2Fm%2F012ts8	01/2004-12/2023
MORENA	Query: %2Fm%2F0_frbfl	01/2004-12/2023
Mortgage Loan	Query: %2Fm%2F0273t5w	01/2004-12/2023
National Action Party	Query: %2Fm%2F01ccsr	01/2004-12/2023
Organized Crime	Query: %2Fm%2F05nsg	01/2004-12/2023
Pandemic	Query: %2Fm%2F061s4	01/2004-12/2023
Particulate Respirator Type N95	Query: %2Fg%2F120tb493	01/2004-12/2023
Party of the Democratic Revolution	Query: %2Fm%2F023bx5	01/2004-12/2023
PEMEX	Query: %2Fm%2F01q3_j	01/2004-12/2023
Petroleum	Query: %2Fm%2F05r_j	01/2004-12/2023
Power Outage	Query: %2Fm%2F01rbhn	01/2004-12/2023
Quarantine	Query: %2Fm%2F069q9	01/2004-12/2023
Recession	Query: %2Fm%2F06bmj	01/2004-12/2023

Reform	Query: %2Fm%2F011bcg4_	01/2004-12/2023
The White House	Query: %2Fm%2F081sq	01/2004-12/2023
Unemployment	Query: %2Fm%2F07s_c	01/2004-12/2023
Unemployment Benefits	Query: %2Fm%2F0218w7	01/2004-12/2023
United States Dollar	Query: %2Fm%2F09nqf	01/2004-12/2023
Vaccine	Query: %2Fm%2F07__7	01/2004-12/2023
Violence	Query: %2Fm%2F0chbx	01/2004-12/2023
Wage	Query: %2Fm%2F01_942	01/2004-12/2023
War	Query: %2Fm%2F082cb	01/2004-12/2023
Water Scarcity	Query: %2Fm%2F0dtw64	01/2004-12/2023
Yahoo! Finance	Query: %2Fm%2F02r91ln	01/2004-12/2023
Panel C. Terms		
Ayotzinapa	Query: Ayotzinapa	01/2004-12/2023
Economic Measures	Query: Medidas Económicas	01/2004-12/2023
Facemask	Query: Cubrebocas	01/2004-12/2023
Insecurity	Query: Inseguridad	01/2004-12/2023
Migrants	Query: Migrantes	01/2004-12/2023
New Outbreak	Query: Rebrote	01/2004-12/2023
Pact	Query: Pacto	01/2004-12/2023
Wall	Query: Muro	01/2004-12/2023

Source: Own elaboration.

3.3 Methodology

3.3.1 Variable Selection Methods

Selecting variables is crucial for forecasting models, as striking a balance between richness and simplicity is essential. According to Stavseth et al. (2020), a model incorporating too few variables might fail to grasp the comprehensive structure of the data. In contrast, a model with excessive variables tends to become overly intricate, fitting individual observations in the dataset too closely, a phenomenon commonly referred to as overfitting. Furthermore, given that we will explore the Dynamic Factor Model (DFM), authors such as Schumacher (2010) and Bantis et al. (2023) support the pre-selection of variables before factor estimation in large datasets. Therefore, without a prior pool of covariates that perform well in predicting IMAI, we resorted to methods widely recognized in the variable selection literature that offer us different ways to select variables; these methods are detailed below.

LASSO. The LASSO method introduced by Tibshirani (1996) consists of an ordinary least squares model (OLS) restricting the sum of the absolute values of estimated coefficients to be less than a constant, allowing some coefficients to zero shrinkage. Let $\boldsymbol{y} = (y_1, \ldots, y_T)'$ a dependent variable, $\boldsymbol{X} = (\boldsymbol{x}_{1,T}, \ldots, \boldsymbol{x}_{P,T})$ an $(T \times P)$ matrix of P potential predictors, where $\boldsymbol{x}_{p,T} = (x_{p,1}, \ldots, x_{p,T})'$, the LASSO setup is as follows:

$$\begin{aligned} \hat{\boldsymbol{\beta}}^{(\text{LASSO})} &= \arg\min_{\boldsymbol{\beta}} \frac{1}{n} ||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 \,, \\ \text{subject to:} &\quad ||\boldsymbol{\beta}||_1 \leq \tau_1, \end{aligned} \tag{3.1}$$

where $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_P)'$ are the coefficients associated with each respective potential predictor, and τ_1 is a tuning parameter. Another way to write the LASSO model is the following:

$$\hat{\boldsymbol{\beta}}^{(\text{LASSO})} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{n} ||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 + \lambda_1 ||\boldsymbol{\beta}||_1 \right\}, \tag{3.2}$$

the Lagrange multiplier λ_1 is also known as the regulation parameter, which determines the amount of shrinkage, since when $\lambda_1 = 0$, the model corresponds to an OLS model, and when $\lambda_1 \to \infty$ the model eliminates all coefficients. Therefore, the model can choose the relevant predictors under this approach and avoid overfitting.

Adaptive LASSO. The LASSO estimation could be inconsistent under certain conditions according Zou (2006). Therefore, the Adaptive LASSO model is proposed, which is based on adding a weight parameter as follows:

$$\hat{\boldsymbol{\beta}}^{\text{(Adaptive LASSO)}} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{n} ||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 + \lambda_1 \sum_{p=1}^{P} w_p |\beta_p| \right\}, \tag{3.3}$$

where $w_p = |\beta_p|^{-\gamma}$ for $\gamma > 0$. With this modification, the LASSO model achieves the oracle property, which establishes consistency in the selection of variables and asymptotic normality. Additionally, adding the weight parameter penalizes the smaller coefficients more severely.

Elastic-Net. Zou & Hastie (2005) identifies that when multicollinearity exists in the model, LASSO chooses only one of the variables that exhibit this characteristic regardless of which one is selected. Furthermore, the LASSO method is not very satisfactory when the number of variables exceeds the number of observations.

On the other hand, The RIDGE regression was introduced by Hoerl & Kennard (1970) to deal with multicollinearity in an OLS model. When covariates exhibit multicollinearity, the variance of the estimated coefficients is large, causing instability and distrust in the estimated coefficients. Hoerl & Kennard (1970) addressing this issue by restricting the sum of the square of estimated coefficients to be less than a constant to reduce the magnitude of regression coefficients that are large or that are correlated with other regression coefficients.

Therefore, the Elastic Net method aims to reduce the complexity of the model by adding the $L1$ penalty and simultaneously deal with the multicollinearity in the covariates by adding the

$L2$ penalty. The standard problem to be solved for the estimated coefficients is added two restrictions as follows:

$$\hat{\boldsymbol{\beta}}^{\text{(ENET)}} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{n} ||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 + \lambda_1 ||\boldsymbol{\beta}||_1 + \lambda_2 ||\boldsymbol{\beta}||_2 \right\}, \tag{3.4}$$

where the Lagrangian multipliers λ_1 and λ_2 are the LASSO and RIDGE regulation parameters, respectively. In this way, the Elastic Net method performs the same time reduction and variable selection but can also choose groups of correlated predictors. Another way to write the Elastic Net model is the following:

$$\hat{\boldsymbol{\beta}}^{\text{(ENET)}} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{n} ||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 + \lambda_1 \left[\alpha ||\boldsymbol{\beta}||_1 + (1-\alpha) ||\boldsymbol{\beta}||_2\right] \right\}, \tag{3.5}$$

where $\alpha \in [0, 1]$. Note that when $\alpha = 0$, the restriction on the penalty $L1$ is removed, so it becomes a RIDGE model, while if $\alpha = 1$, the restriction on the penalty $L2$ is removed, so it becomes a purely LASSO model.

Adaptive Elastic-Net. Although the Elastic Net model deals well with high dimensionality and multicollinearity in the data, it lacks the Oracle property, which is satisfied by the Adaptive LASSO model. In order to acquire the oracle property and deal with collinearity in the data, the Adaptive Elastic Net method is proposed by Zou & Zhang (2009), which combines the adaptive weights to the $L1$ norm penalty and the $L2$ norm, improving in both directions, that is, achieving the oracle property and dealing with high dimensionality and multicollinearity in the data, which results in the following system:

$$\hat{\boldsymbol{\beta}}^{\text{(A-ENET)}} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{n} ||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 + \lambda_1 \left[\alpha \sum_{p=1}^{P} w_p|\beta_p| + (1-\alpha) \sum_{p=1}^{P} \beta_p^2 \right] \right\}, \tag{3.6}$$

where w_p is defined as in the Adaptive Lasso model. In this way, the Adaptive Elastic Net guarantees the consistency and asymptotic normality properties as the Adaptive LASSO and can simultaneously deal with the multicollinearity problem.

3.3.2 Dynamic factor model

The DFM summarizes the information in a set of predictors using a few common factors. The use of dynamic factors for nowcasting macroeconomic variables became popular from the work of Giannone et al. (2008), where later Doz et al. (2011) developed the statistical theory behind it. DFM aims to separate each observation of a series into two orthogonal unobserved components. The first captures the cross-sectional co-movements across the series, and the second captures the idiosyncratic component. The DFM can be written for each predictor as:

$$\boldsymbol{X}' = \boldsymbol{\Lambda F} + \boldsymbol{\eta} \tag{3.7}$$

where $\boldsymbol{F} = (\boldsymbol{f}_1, \ldots, \boldsymbol{f}_R)'$ is a stationary process of common factors, with $\boldsymbol{f}_r = (f_{r,1}, \ldots, f_{r,t})'$, $\boldsymbol{\Lambda}$ is an $(P \times R)$ matrix of factor loadings for each predictor, and $\boldsymbol{\eta}$ is a stationary process of idiosyncratic errors. Common factors and idiosyncratic components are considered to be orthogonal. Moreover, factors are modeled as a vector auto-regressive (VAR) process of order $N < T$, where for each $r = 1, \ldots, R$,

$$f_{r,t} = \sum_{i=1}^{R} \sum_{n=0}^{N} \psi_{i,t}^{(r)} f_{i,t-n} + \epsilon_{r,t}, \qquad \text{for } t = 1, \ldots, T, \tag{3.8}$$

where each $\psi_{i,u}^{(r)}$ is an auto-regressive parameter, with $\psi_{r,0}^{(r)} = 0$ for each $r = 1, \ldots, R$, and $\epsilon_{r,t} \sim \mathcal{N}(0, \sigma_r^2)$ is a white noise process of shocks to factors.

On the other hand, when the database has “jagged edges,” the methodology of Doz et al. (2011) is employed, which consists of estimating the common factor(s) in two steps. In the first step, the model parameters are estimated using the available information, and the common factors obtained are treated as the true ones. The common factors are obtained in the second step via the Kalman smoother.

3.4 IMAI nowcasting

In this section, we describe the routine for IMAI nowcasting. We start by telling how we treat the database. Subsequently, we apply the variable selection methods and use the selected variables through different models that point to the IMAI nowcast. Finally, we used the mean absolute error (MAE) and the Diebold-Mariano test to compare the performance of the models.

3.4.1 Data treatment

As we mentioned, some traditional variables were obtained seasonally adjusted directly from their source, while the rest we adjusted for seasonality using X-13ARIMA-SEATS. Once all the traditional variables are adjusted for seasonality, we apply transformations that maximize the correlation with the IMAI.

To ensure appropriate transformations, we divided the traditional variables into two groups: those measured in percentages or on a 0 - 100 scale and those not. For the variables measured in percentage or on a scale of 0 - 100, we apply the transformations: None (N), Monthly Difference (MD), and Annual Difference (AD), while to the rest of the variables, we apply the transformations: None (N), Monthly Percentage Variation (MPV) and Annual Percentage Variation (APV).

We observe that the transformations may change as the data is updated. For instance, consider the variable "Right Time to Invest: Manufacturing." The N transformation maximizes its correlation with the IMAI from November 2011 to March 2021. However, from April 2021 to December 2023, the AD transformation is the one that maximizes the correlation. Therefore, it is advisable to update the transformations periodically. However, care must be taken when there are abrupt changes, since during the period of the COVID-19 pandemic, the transformation that maximizes the correlation with the IMAI for some variables changed and then returned to the transformation that maximized its correlation with the IMAI before that period.

To deal with this, we employ a heuristic algorithm that allows the transformation to be updated as the sample is updated but resists changing transformations if a particular transformation has maximized its correlation in recent periods; this process is shown in Table 3.3, which also shows how we deal with Google's online search indexes.

Regarding Google's online search indexes, some observations contain "< 1", which implies that the search volume of such index has been very low, but not zero, so these observations are replaced with 0.5. Furthermore, as mentioned above, the search indexes provided by Google are presented on a scale of 0 - 100, where 0 is the value assigned when no searches are associated with the category/topic/term in the timespan. At the same time, 100 implies that it has reached maximum interest in the search. For building a pseudo-real-time database in the routine process, each Google search index is normalized each index (see Step 4.3 in Table 3.3) as in Corona et al. (2021). Afterward, following Kohns & Bhattacharjee (2023), we use the LOESS filter using the `STL` package to decompose the series into three components: trend, seasonal, and residual; we remove the seasonal component. Finally, we transformed each normalized Google search index using the transformation that maximizes its correlation with the IMAI over the past three years.

Ultimately, we will have a seasonal adjusted pseudo-real-time database with 165 potential predictors, 77 traditional and 88 non-traditional, transformed to maximize their correlation with the IMAI for each period.

3.4.2 Variable Selection and the Common Factor

We require a balanced database to implement the variable selection methods mentioned in Section 3.3. For this purpose, we first normalize both the potential predictors and the dependent variable. Then, we use the Kalman smoother to retropolate the missing values to get a balanced database using `imputeTS` package. Once we obtain the balanced database, we implement the variable selection methods mentioned previously.

Table 3.3: Data treatment

1. Let: $\boldsymbol{Z} = (\boldsymbol{z}_{1,T}, \ldots, \boldsymbol{z}_{77,T})$ a vector of seasonally adjusted traditional variables.
2. **for** $i = 1$ to 77 **do**:
    - Split the variable $\boldsymbol{z}_{i,t}$ for $t = T - 12H + \tau$, for some $H \in \mathbb{N}$.
    - **for** $\tau = 0$ to $12H - 1$ **do**:
        - Apply: $N(\boldsymbol{z}_{i,t})$, $M(\boldsymbol{z}_{i,t})$, and $A(z_{i,t})$.
        - Compute: $\rho^N_{i,\tau} = |\text{cor}(\boldsymbol{y}_t, N(\boldsymbol{z}_{i,t}))|$.
        - Compute: $\rho^M_{i,\tau} = |\text{cor}(\boldsymbol{y}_t, M(\boldsymbol{z}_{i,t}))|$.
        - Compute: $\rho^A_{i,\tau} = |\text{cor}(\boldsymbol{y}_t, A(\boldsymbol{z}_{i,t}))|$.
    - **end**
    - Let: $f(\cdot) = \text{argmax}_{\{N(\cdot),M(\cdot),A(\cdot)\}} \frac{1}{12H} \left\{ \sum_{\tau=0}^{12H-1} \rho^N_{i,\tau}, \sum_{\tau=0}^{12H-1} \rho^M_{i,\tau}, \sum_{\tau=0}^{12H-1} \rho^A_{i,\tau} \right\}$.
    - Construct: $\boldsymbol{x}_{i,T} = f(\boldsymbol{z}_{i,T})$

   end
3. Let $\boldsymbol{G} = (\boldsymbol{g}_{1,T}, \ldots, \boldsymbol{g}_{88,T})$ a vector of Google search indexes.
4. **for** $k = 1$ to 88 **do**:
    - Let: $\boldsymbol{g}_{k,T} = (g_{k,1}, \ldots, g_{k,T})'$.
    - **if** $g_{k,t} =$ "< 1" for some $t = 1, \ldots, T$ **replace** $g_{k,t} = 0.5$.
    - Define: $\boldsymbol{\mathcal{G}}_{k,T} = \lfloor \boldsymbol{g}_{k,T} / \max\{\boldsymbol{g}_{k,T}\} \rceil$.
    - Apply: LOESS filter to decompose as $\boldsymbol{\mathcal{G}}_{k,T} = \boldsymbol{\mathcal{T}}_{k,T} + \boldsymbol{\mathcal{S}}_{k,T} + \boldsymbol{\mathcal{R}}_{k,T}$.
    - Define: $\bar{\boldsymbol{g}}_{k,T} = \boldsymbol{\mathcal{T}}_{k,T} + \boldsymbol{\mathcal{R}}_{k,T}$
    - Split the variable $\bar{\boldsymbol{g}}_{k,t}$ for $t = T - 12H + \tau$.
    - **for** $\tau = 0$ to 12H-1 **do**:
        - Apply: $N(\bar{\boldsymbol{g}}_{k,t})$, $M(\bar{\boldsymbol{g}}_{k,t})$, and $A(\bar{\boldsymbol{g}}_{k,t})$.
        - Compute: $\rho^N_{k,\tau} = |\text{cor}(\boldsymbol{y}_t, N(\bar{\boldsymbol{g}}_{k,t}))|$.
        - Compute: $\rho^M_{k,\tau} = |\text{cor}(\boldsymbol{y}_t, M(\bar{\boldsymbol{g}}_{k,t}))|$.
        - Compute: $\rho^A_{k,\tau} = |\text{cor}(\boldsymbol{y}_t, A(\bar{\boldsymbol{g}}_{k,t}))|$.
    - **end**
    - Let: $f(\cdot) = \text{argmax}_{\{N(\cdot),M(\cdot),A(\cdot)\}} \frac{1}{12H} \left\{ \sum_{\tau=0}^{12H-1} \rho^N_{k,\tau}, \sum_{\tau=0}^{12H-1} \rho^M_{k,\tau}, \sum_{\tau=0}^{12H-1} \rho^A_{k,\tau} \right\}$.
    - Construct: $\boldsymbol{x}_{62+k,T} = f(\bar{\boldsymbol{g}}_{k,T})$.

   end
5. Construct: $\boldsymbol{X} = (\underbrace{\boldsymbol{x}_{1,T}, \ldots, \boldsymbol{x}_{77,T}}_{\text{Traditional}}, \underbrace{\boldsymbol{x}_{78,T}, \ldots, \boldsymbol{x}_{165,T}}_{\text{Non-Traditional}})$.

In practice, a set of hyperparameters is proposed as candidates to estimate the LASSO and Elastic Net models (as well as their Adaptive versions); subsequently, through cross-validation (CV), those hyperparameters that minimize or maximize some accuracy metric are chosen as optimal. The CV splits the database into k-folds, a random fold is chosen to train the model, and it is validated on the remaining sample. However, when it comes to time series, if the model is trained on a fold, it must be validated with data that is in time ahead of that fold by the data time dependence.

Therefore, we propose a λ's grid for all variable selection models and an α's grid for Elastic Net and Adaptive Elastic Net models. Next, we create time-slices where each time-slice has size $T - 12H + h$, with $H \in \mathbb{N}$ and for $h = 0, \ldots, 12H - 2$[1]. Each model is trained on each time slice and validated on the next period. Afterward, we obtain the hyperparameters of each model that minimize the MAE during the training period; this process is carried out with the packages `caret` and `glmnet`. Finally, with the optimal hyperparameters, the model is estimated with the database up to the observation in $T - 1$, and the estimated coefficients of each variable are obtained. To construct the common factors with the `dynfactoR` package associated with each variable selection model, we use the covariates such that their estimated coefficient differs from zero. The variable selection and construction process is detailed in Table 3.4.

3.4.3 Training and Test Models

For the IMAI Nowcasting methodology, we present a suite of eight models. Four incorporate LASSO, Adaptive LASSO, Elastic Net, and Adaptive Elastic Net techniques integrated with ARMA error structures to mitigate autocorrelation effects. Simultaneously, the remaining four employ linear models with ARMA errors, utilizing a single common factor derived from the variable selection process of each method above.

As previously delineated, we employ each variable selection model alongside its respective

[1]The last time-slice has size $T - 2$ since the model is validated in the next period and in pseudo-real-time the dependent variable is available up to $T - 1$.

Table 3.4: Variable selection and construction of common factors

1. Let: $\boldsymbol{X}=(\boldsymbol{x}_{1,T},\ldots,\boldsymbol{x}_{150,T})$ a vector of potential predictors with missing values.
2. Apply: Kalman smoother over normalized $\boldsymbol{X}$ to retropolate the missing values.
3. Let: $\bar{\boldsymbol{X}}$ the balanced normalized matrix of potential predictors.
4. **for** $a = 1$ to 20 **do**:
    - **for** $l = 0$ to 200 **do**:
        - **for** $h = 0$ to $12H - 2$ **do**:
            - Split database until $t = T - 12H + h$.
            - Run: ENET with $\alpha = 0.05a$ and $\lambda = 10^{(-5+0.05l)}$.
            - Get: $\hat{\boldsymbol{\beta}}^{\text{(ENET)}}_{a,l,h}$ and $\hat{y}_{t+1}$ to Compute: $\text{AE}^{\text{(ENET)}}_{a,l,h} = |y_t - \hat{y}_{t+1}|$.
        - **end**
        - **Compute:** $\text{MAE}^{\text{(ENET)}}_{a,l} = \frac{1}{12H-1}\sum_{h=0}^{12H-2}\text{AE}^{\text{(ENET)}}_{a,l,h}$
    - **end**

    end
5. Define: $(\alpha^{*\text{(ENET)}}, \lambda^{*\text{(ENET)}}) = (0.05a^*, 10^{(-5+0.05l^*)})$, where $(a^*, l^*) = \arg\min_{\{a,l\}} \text{MAE}^{\text{(ENET)}}_{a,l}$.
6. Define: $\lambda^{*\text{(RIDGE)}} = 10^{(-5+0.05l^*_R)}$, where $l^*_R = \arg\min_l \text{MAE}^{\text{(ENET)}}_{0,l}$.
7. Define: $\lambda^{*\text{(LASSO)}} = 10^{(-5+0.05l^*_L)}$, where $l^*_L = \arg\min_l \text{MAE}^{\text{(ENET)}}_{1,l}$.
8. Split database until $T - 1$.
9. Run: ENET with $\alpha = \alpha^{*,\text{ENET}}$ and $\lambda = \lambda^{*\text{(ENET)}}$ using data in **Step (8)**.
10. Get: $\beta^{*\text{(ENET)}}$.
11. Run: RIDGE with $\alpha = 0$ and $\lambda = \lambda^{*\text{(RIDGE)}}$ using data in **Step (8)**.
12 Get: $\beta^{*\text{(RIDGE)}}$ and $w^{\text{(RIDGE)}} = |\boldsymbol{\beta}^{*\text{(RIDGE)}}|^{-\gamma}$.
13. Run: LASSO with $\alpha = 1$ and $\lambda = \lambda^{*\text{(LASSO)}}$ using data in **Step (8)**.
14. **for** $a = a^*$ or 1 **do**:
    - **for** $l = 0$ to 200 **do**:
        - **for** $h = 0$ to $12H - 2$ **do**:
            - Split database until $t = T - 12H + h$.
            - Run: A-ENET with $\alpha = 0.05a$, $\lambda = 10^{(-5+0.05l)}$, and $w = w^{\text{(RIDGE)}}$.
            - Get: $\hat{\boldsymbol{\beta}}^{\text{(A-ENET)}}_{a,l,h}$ and $\hat{y}_{t+1}$ to Compute: $\text{AE}^{\text{(A-ENET)}}_{a,l,h} = |y_t - \hat{y}_{t+1}|$.
        - **end**
        - **Compute:** $\text{MAE}^{\text{(A-ENET)}}_{a,l} = \frac{1}{12H-1}\sum_{h=0}^{12H-2}\text{AE}^{\text{(A-ENET)}}_{a,l,h}$
    - **end**

    end
15. Define: $\lambda^{*\text{(A-ENET)}} = 10^{(-5+0.05l^{**})}$, where $l^{**} = \arg\min_l \text{MAE}^{\text{(A-ENET)}}_{a,l}$.
16. Define: $\lambda^{*\text{(A-LASSO)}} = 10^{(-5+0.05l^{**}_L)}$, where $l^{**}_L = \arg\min_l \text{MAE}^{\text{(ENET)}}_{1,l}$.
17. Run: A-ENET with $\alpha = \alpha^{*,\text{ENET}}$, $\lambda = \lambda^{*\text{(A-ENET)}}$, and $w = w^{\text{(RIDGE)}}$ using data in **Step (8)**.
18. Get: $\beta^{*\text{(A-ENET)}}$.
19. Run: A-LASSO with $\alpha = 1$, $\lambda = \lambda^{*\text{(A-LASSO)}}$, and $w = w^{\text{(RIDGE)}}$ using data in **Step (8)**.
20. Get: $\beta^{*\text{(A-LASSO)}}$.
21. Define: $\boldsymbol{X}^{(M)} = \{\boldsymbol{x}_{p,T} \in \boldsymbol{X} : \beta^{(M)}_p \neq 0\}$ for $M = \{\text{ENET, LASSO, A-ENET, A-LASSO}\}$
22. Run: DFM using $\boldsymbol{X}^{(M)}$ with $R = 1$ and $N = 1$.
23. Get: a single common factor $\boldsymbol{f}^{(M)}_T$ using two-step methodology for each $\boldsymbol{X}^{(M)}$.

optimized parameters acquired through the training regimen depicted in Table 3.4. It is pertinent to note that, to prevent redundancy with the content of Section 3.3, only the configuration of the Adaptive Elastic Net model is illustrated herein, as it encapsulates the overarching framework of the other variable selection models; therefore the general training model is as follows:

$$\begin{aligned}
& y_t = \sum_{p=1}^{P} \beta_p x_{p,t} + \epsilon_t, \\
& \text{subject to:} \quad \sum_{p=1}^{P} |w_p \beta_p| \leq \tau_1 \quad \text{and} \quad \sum_{p=1}^{P} \beta_p^2 \leq \tau_2, \\
& \text{with:} \quad \epsilon_t = \sum_{p=1}^{\mathcal{P}} \theta_p \epsilon_{t-p} + \vartheta_t + \sum_{q=1}^{\mathcal{Q}} \phi_q \vartheta_{t-q}, \\
& \text{for:} \quad t = 1, \ldots, T-1.
\end{aligned} \tag{3.9}$$

The nowcast for the dependent variable in the pseudo-current period T using variable selection models with the estimated parameters $\hat{\beta}_1, \ldots, \hat{\beta}_P$, $\hat{\theta}_1, \ldots, \hat{\theta}_{\mathcal{P}}$, $\hat{\phi}_1, \ldots, \hat{\phi}_{\mathcal{Q}}$, is given by:

$$\hat{y}_T = \sum_{p=1}^{P} \hat{\beta}_p x_{p,T} + \sum_{p=1}^{\hat{\mathcal{P}}} \hat{\theta}_p \varepsilon_{T-p} + \sum_{q=1}^{\hat{\mathcal{Q}}} \hat{\phi} \vartheta_{T-q}. \tag{3.10}$$

Similarly, the setup of the training model using a single common factor as a regressor is as follows:

$$\begin{aligned}
& y_t = \gamma_0 + \gamma_1 f_t^{(M)} + \varepsilon_t \\
& \text{with:} \quad \epsilon_t = \sum_{p=1}^{\mathcal{P}'} \theta_p \epsilon_{t-p} + \vartheta_t + \sum_{q=1}^{\mathcal{Q}'} \phi_q \vartheta_{t-q}, \\
& \text{for:} \quad t = 1, \ldots, T-1.
\end{aligned} \tag{3.11}$$

The nowcast for the dependent variable in the pseudo-current period T using a common factor obtained by the variable selection model $M = \{$LASSO, A-LASSO, ENET, A-ENET$\}$ with the estimated parameters $\hat{\gamma}_0, \hat{\gamma}_1, \hat{\theta}_1, \ldots, \hat{\theta}_{\mathcal{P}'}, \hat{\phi}_1, \ldots, \hat{\phi}_{\mathcal{Q}'}$, is given by:

$$\hat{y}_T = \hat{\gamma}_0 + \hat{\gamma}_1 f_T^{(M)} + \sum_{p=1}^{\hat{\mathcal{P}}'} \hat{\theta}_p \varepsilon_{T-p} + \sum_{q=1}^{\hat{\mathcal{Q}}'} \hat{\phi} \vartheta_{T-q}. \tag{3.12}$$

Finally, we use the mean absolute error (MAE) to measure the accuracy of the generated nowcasts by each variable selection method and each common factor constructed by each variable selection method.

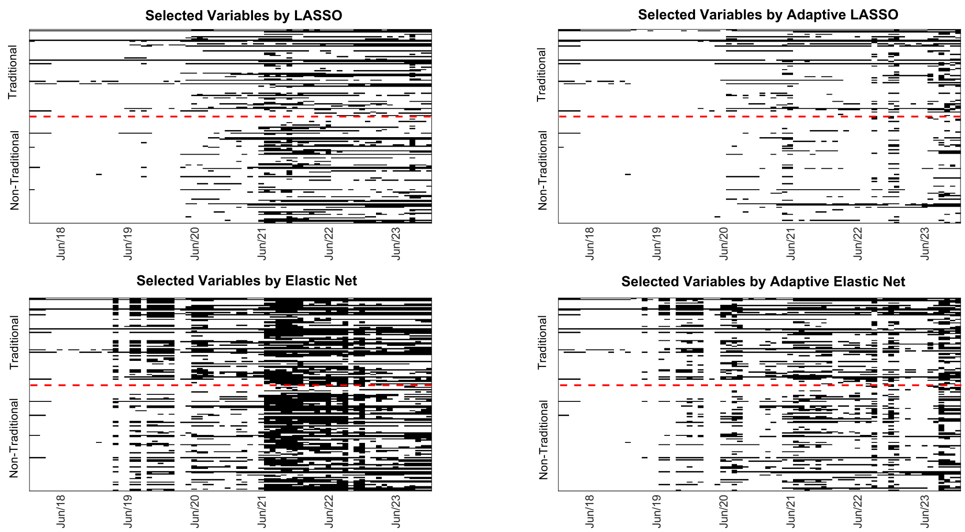
3.5 Results

The methodology is implemented from January 2018 to December 2023 to measure the accuracy of the nowcasts in two years of high uncertainty: the COVID-19 pandemic in 2020, its recovery in 2021, and two periods before and after this event. We use $H = 5$, which implies that the performance of the variable selection models has been validated over the past five years. Furthermore, the variables' transformations are chosen with the one that maximizes the correlation with the IMAI during the last five years.

We begin by showing the sets of variables selected for each period by each method shown in Section 3.3 in Figure 3.1. Each graph represents a grid of the form: period on the x-axis and potential predictor on the y-axis, where the black boxes indicate that in the indicated period on the x-axis, the corresponding variable on the y-axis was selected by one of the methods described by Table 3.4. Given the size of the initial data set, it isn't easy to place the labels of each variable's name in the graph, so we place a horizontal line to separate the potential predictors by traditional and non-traditional only to illustrate the frequency with which certain variables are selected.

As expected, Adaptive methods show cleaner variable selection than their non-adaptive versions. On the other hand, the LASSO method selects fewer variables than the Elastic Net method, in the same way the Adaptive LASSO with the Adaptive Elastic Net. We can notice that as time

Figure 3.1: Selected Variables



progresses, the selection of variables becomes more intense for the four methods, particularly pronounced during the quarantine period due to the COVID-19 pandemic. However, the Elastic Net methods and their Adaptive version begin in mid-2019. Furthermore, we observe that at least three variables are frequently selected and belong to the set of traditional indicators.

In Table 3.5, we show the 25 most selected indicators by all methods and their selection frequency, where at least three non-traditional indicators appear above 50% of the test period. Among the most selected Google search indexes are topics related to politics and the consequences of the COVID-19 pandemic. As for the hard indicators, those related to the automotive, manufacturing, and industrial activities in the United States are mostly selected.

Once the variables are selected in a period, the common factors are built, the linear model is trained, and the forecast is carried out in the period T. The parameters of the linear models with a single common factor as a regressor are estimated by maximum likelihood. The performance of each model is evaluated using the MAE accuracy metric and compared with a naive ARMA model. The results of the out-of-sample estimation are shown in Table 3.6. The first result is that all models outperform the Naive model, and all variable selection models outperform the models that use a common factor as a regressor. The models that show better and equal performance

Table 3.5: The Top 25 of the Most Selected Indicators

Indicator	**Frequency**	**Source**
Production: Cars	100%	INEGI
Expected RGDP by Private Sector Economics Specialists	98%	BANXICO
Manufacturing Production Index: USA	91%	FRED
Production: Trucks	73%	INEGI
Unemployment Rate: USA	72%	FRED
Sales: Convenience and Department Stores	70%	ANTAD
Employment: Construction	67%	INEGI
Production: Manufacturing	67%	IMEF
Unemployment	61%	Google
Producer Price Index: Secondary Activities	55%	INEGI
Manufacturing Order Index	55%	INEGI
Sales: Cars	53%	INEGI
National Action Party	51%	Google
Foreclosure	50%	Google
Employment: Mexican Institute of Social Security	49%	IMSS
Unemployment Benefits	48%	Google
Industrial Production Index: USA	47%	FRED
Amount Traded: Interbank Electronic Payment System	45%	BANXICO
Politics	44%	Google
Hotels & Accommodations	40%	Google
Corruption	40%	Google
Aggregate Trend Index: Construction	40%	INEGI
New Outbreak	38%	Google
Citizens' Movement	38%	Google
Final Goods Inventories: Manufacturing	36%	IMEF

Source: Own elaboration.
Note: The frequency represents the percentage of times the indicator is selected by all methods throughout the analysis period.

Table 3.6: Model's Performance

Model	MAE	Average Selection		
		Traditional	**Non-Traditional**	**Total (%)**
Naive	2.41	—	—	—
LASSO	1.25	16.5	14.0	18.5%
Adaptive LASSO	1.54	10.7	4.6	9.2%
Elastic Net	1.25	29.9	28.0	35.1%
Adaptive Elastic Net	1.48	19.7	13.1	19.8%
LASSO & DFM	1.67	16.5	14.0	18.5%
Adaptive LASSO & DFM	1.64	10.7	4.6	9.2%
Elastic Net & DFM	1.77	29.9	28.0	35.1%
Adaptive Elastic Net & DFM	1.78	19.7	13.1	19.8%

Source: Own elaboration.

are the LASSO and Elastic Net models.

In Figure 3.2, we present the cumulative Mean Absolute Error (MAE) over the analysis period. The graph illustrates that initially, the models exhibit comparable performance, with notable prominence from the dynamic factors model constructed using variables selected by the Elastic Net method. As the pandemic unfolds in April 2020, a divergence in performance among the models becomes apparent, with both the previously mentioned model and the Adaptive Elastic Net model continuing to excel. However, during the April 2021 rebound, most models displayed erratic responses, while the LASSO and Elastic Net models responded more accurately. Subsequently, significant disparities emerge in the performance of the models from that point onward.

The one-step nowcast of the two best models (LASSO and Elastic Net) along with IMAI is shown in Figure 3.3; here we can notice that the performance of both models is accurate and they are quite similar, the largest error that the models exhibit is during April 2020 where the quarantine period induced by the authorities began. As shown in Figure 3.1, Google search indexes begin to gain relevance in May 2020, and the model recovers the direction of the nowcasts.

Figure 3.2: Cumulative MAE

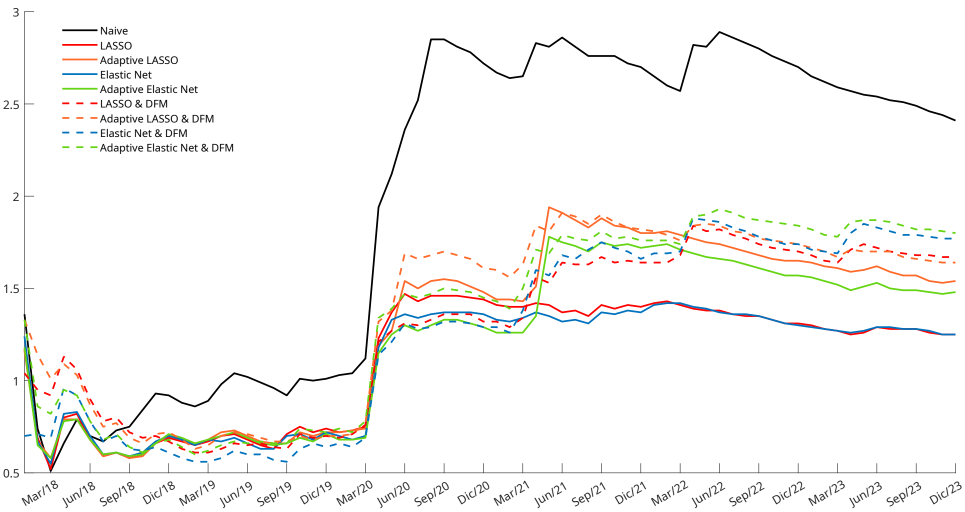
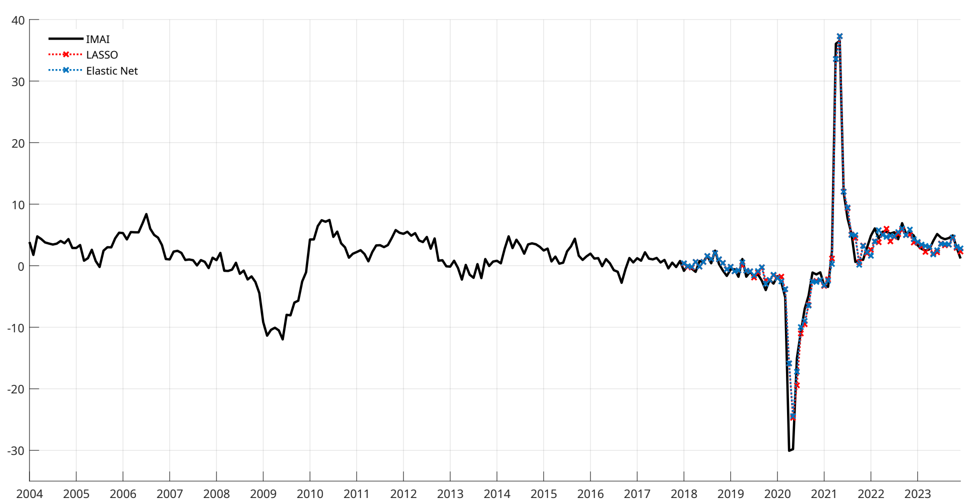


Figure 3.3: Best Models' Performance



3.6 Conclusion

The research presented in this article enriches the existing body of literature concerning the implementation of nowcasts for the IMAI, a crucial factor in accurately predicting both the IGAE and GDP. In pursuit of this objective, we employ a blend of traditional indicators, selected for their timeliness and strong correlation, supported with big data from non-traditional indicators such as online searches from the Google search engine. These non-traditional indicators involve topics related to the structural characteristics of the Mexican economy, the search for employment, and investment opportunities, which are boosted in economic recessions or booms.

However, a large pool of potential predictors risks overfitting, so we filter the indicators through variable selection models such as LASSO, Adaptive LASSO, Elastic Net, and Adaptive Elastic Net. Additionally, we use dynamic factor models that summarize a large amount of information into fewer common factors constructed from variable selection methods.

Among the main results, we highlight the importance of big data in periods of recession as it increases its participation in variable selection models above other hard indicators. The LASSO and Elastic Net models are the ones that exhibit the best performance in the analysis period. This result is relevant since these models do not select the least variables, highlighting the importance of the large data set.

Selecting between the LASSO and Elastic Net models for nowcasting the IMAI presents a significant challenge. The Elastic Net model offers a broader scope for selecting variable combinations due to its utilization of two regularization parameters. This flexibility potentially leads to the identification of superior models. However, this advantage comes at the cost of increased computational complexity. In contrast, the LASSO model, reliant on a single hyperparameter, offers computational efficiency but provides fewer alternatives for parameter combinations. Moreover, the LASSO model favors a more parsimonious selection of variables than the Elastic Net.

Continued application of this methodology in future exercises is crucial, alongside exploring alternative variable selection models like Stochastic Search Variable Selection. Unlike conventional methods, Stochastic Search Variable Selection adopts a Bayesian approach, assigning probabilities to each indicator. This nuanced approach enables us to prioritize indicators based on relevance, offering a more refined understanding of their impact on forecasting accuracy. Integrating such advanced models into our analysis enhances the interpretability and robustness of our predictions, paving the way for more informed decision-making in economic forecasting.

On the other hand, it is no surprise that the LASSO and Elastic Net models have outperformed the dynamic factor models, given their training emphasis on minimizing MAE through their selection process. This insight provides a springboard for future research to explore optimizing hyperparameters to minimize MAE while incorporating the common factor constructed from the selected variables. Such investigations hold the potential to refine predictive accuracy further and represent a promising direction for advancing the field.

General Conclusions

This dissertation consists of three chapters, analyzes the impact of fiscal policy on a government with high debt in economic recessions, the role of informal employment in the main macroeconomic aggregates during the COVID-19 crisis, and the use of models for the immediate forecast of the IMAI, a key indicator in the timely monitoring of economic activity.

Chapter 1 suggests an alternative fiscal policy for governments facing high debt levels to stimulate economic activity during recessions. This policy involves reallocating government spending by reducing expenditures with lower multiplier effects to finance activities with a greater impact on economic output. The study finds this budget redistribution approach to be an effective countercyclical fiscal stimulus that simultaneously acts as a fiscal consolidation measure with favorable implications for long-term public finances.

However, this policy comes with social costs, particularly for households heavily reliant on government transfers as a significant portion of their income (non-savers). Implementing spending cuts may generate political pressure due to potential voter dissatisfaction. Additionally, we note that changes in fiscal policy, unlike monetary policy, require more time to enact due to the need for legislative approval, which may delay or prevent execution.

The model presented in Chapter 1 has several limitations that could be addressed in future research, such as excluding the informal sector's impact on fiscal policy multipliers and not accounting for the external sector's influence on the size of fiscal multipliers. Incorporating these factors and the effects of oil revenues on the government's budget constraint could enhance the model's accuracy in the Mexican context.

Chapter 2 analyzes the impact of the informal sector on economic growth, employment, and inflation during the COVID-19 crisis. In this chapter, it is concluded that the presence of the informal sector in the economy in the face of a health crisis cushions the inflationary effect derived from the impact of post-confinement policy but faces large economic and employment losses, consistent with the empirical evidence in the pandemic period. Regarding well-being, families in this economy would prefer to live in a scenario without informality since they are unwilling to exchange economic and employment stability for price stability.

The channel through which the informal sector operates causes the effects on economic growth, employment, and inflation mentioned above due to its low entry costs, i.e., high flexibility and tax-free payroll. The high flexibility allows for greater employment outflows at the time of impact and greater inflows in the recovery phase. As a result, the strong job losses driven by the confinement policy cause greater contractions in GDP. On the other hand, the informal sector's ability to evade taxes means that the government has less room to alleviate the economy, so it does not reduce lump-sum taxes as much as when informality is absent. This further reduces households' disposable income, which prevents them from smoothing their consumption and, therefore, generates a buffer effect on inflation.

These results highlight the importance of promoting formal employment in Latin American and Caribbean countries through targeted public policies. These policies aim to reduce labor informality, which can mitigate negative impacts on GDP and employment during crises like the recent one caused by the COVID-19 pandemic. Additionally, the strategy ensures a safer work environment for workers and households by implementing safeguards and protections. The results suggest considering global supply chain effects, economic sector dependence, and vaccination risk perception for a more comprehensive analysis.

Chapter 3 presents a machine learning model for IMAI nowcasting using traditional indicators (economic, financial, and survey-based) and non-traditional indicators (Google search indices).

We filtered covariates using variable selection methods (such as LASSO, Adaptive LASSO, Elastic Net, and Adaptive Elastic Net) to avoid model overfitting. Additionally, we used a dynamic factor model (DFM) that produces a common factor of the covariates selected using the above selection methods.

The LASSO and Elastic Net models outperform the previous ones and yield similar performances using the MAE metric. However, the LASSO method incurs lower computational costs since it relies on one hyperparameter, while the Elastic Net uses two hyperparameters, which incurs higher computational costs. Furthermore, as a variable selector, the LASSO selects smaller sets of covariates. In contrast, the Elastic Net method determines the largest sets of covariates. Therefore, the LASSO model favors the parsimony of the prediction model.

Furthermore, this work highlights the use of non-traditional indicators, such as Google Trends Indexes, particularly during the pandemic, since these became more frequent in selecting variables from this period onwards, providing major predictive power to the model.

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