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Fiscal and Monetary Dominance in Brazil: A Machine Learning DSGE Approach

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Ata da reunião da Banca Examinadora designada para avaliar o trabalho de dissertação do mestrando **Kleiton de Luna Souza da Silva**, submetida para obtenção do grau de mestre em Economia, área de concentração em **Economia Aplicada.**

Aos vinte dias, do mês de fevereiro, do ano dois mil e vinte e seis, às catorze horas, no Programa de Pós-Graduação em Economia, do Centro de Ciências Sociais Aplicadas, da Universidade Federal da Paraíba, reuniram-se, em cerimônia pública, os membros da Banca Examinadora, constituída pelos professores doutores **Edilean Kleber da Silva Bejarano Aragón** (Orientador), da Universidade Federal da Paraíba; **Alejandro Cayetano Garcia Cintado** (Coorientador), da Universidade Federal da Paraíba; **Cássio da Nóbrega Besarria** (Examinador Interno), da Universidade Federal da Paraíba, **Celso José Costa Júnior** (Examinador Externo) da Universidade Estadual de Ponta Grossa, a fim de examinarem o candidato ao grau de mestre em Economia, área de concentração em **Economia Aplicada**, **Kleiton de Luna Souza da Silva.** Além dos examinadores e do examinando, compareceram também, representantes do Corpo Docente e do Corpo discente. Iniciando a sessão, o professor **Edilean Kleber da Silva Bejarano Aragón**, na qualidade de presidente da Banca Examinadora, comunicou aos presentes a finalidade da reunião e os procedimentos de encaminhamento desta. A seguir, concedeu a palavra ao candidato, para que fizesse oralmente a exposição do trabalho, apresentado sob o título: **"Fiscal and monetary dominance in Brazil:A machine learning dsge approach"**. Concluída a exposição, o senhor presidente solicitou que fosse feita a arguição por cada um dos examinadores. A seguir foi concedida a palavra ao candidato, para que respondesse e esclarecesse as questões levantadas. Terminadas as arguições, a Banca Examinadora passou a proceder à avaliação e ao julgamento do candidato. Em seguida, o senhor presidente comunicou aos presentes que a Banca Examinadora, por unanimidade, **aprovou** a dissertação apresentada e defendida com o conceito **APROVADO**, concedendo assim, o grau de **Mestre em Economia**, área de concentração em **Economia Aplicada**, ao mestrando **Kleiton de Luna Souza da Silva.** E, para constar, eu, **Ivone Dias da Silva**, secretária *ad hoc* do Programa de Pós-Graduação em Economia, lavrei a presente ata, que assino junto com os membros da Banca Examinadora. João Pessoa, 20 de fevereiro de 2026.

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Em memória de Marcus Oliveira de Souza e Ivanize de Luna Souza

Abstract

This dissertation investigates the interactions between fiscal and monetary policies in Brazil using a hybrid approach that combines Markov-switching DSGE models (MS-DSGE) and supervised machine learning techniques. The structural model serves as a data-generating process to train classification algorithms, which are subsequently applied to real Brazilian time series. Among the tested models, XGBoost demonstrated superior performance, achieving an accuracy of 95% and a Log Loss of 0.17 on the test set. The results reveal a dynamic chronology: Brazil operated under fiscal dominance between 2013 and 2015, transitioning to monetary dominance in the 2015-2017 period following the implementation of the expenditure ceiling. An original contribution of this work is the identification of an explosive regime during the pandemic (2020Q3-2021Q3), characterized by the simultaneously active stance of both fiscal and monetary authorities. Robustness analyses indicate that the identification of fiscal and explosive regimes is resilient to different filtering techniques, whereas monetary dominance appears more sensitive to modeling assumptions. The findings suggest a return to fiscal dominance in the most recent period.

Keywords: Regime Switching; DSGE; Fiscal Dominance; Monetary Dominance; Machine Learning.

Resumo

A presente dissertação investiga as interações entre as políticas fiscal e monetária no Brasil utilizando uma abordagem híbrida que combina modelos DSGE com mudança de regime (MS-DSGE) e técnicas de aprendizado de máquina supervisionadas. O modelo estrutural é empregado como processo gerador de dados para treinar algoritmos de classificação, que são posteriormente aplicados a séries temporais reais da economia brasileira. Entre os modelos testados, o XGBoost apresentou o desempenho superior, atingindo uma acurácia de 95% e um Log Loss de 0,17 no conjunto de teste. Os resultados revelam uma cronologia dinâmica: o Brasil operou sob dominância fiscal entre 2013 e 2015, migrando para dominância monetária no período 2015-2017 após a implementação do teto de gastos. Uma contribuição central deste trabalho é a identificação de um regime explosivo durante a pandemia de COVID-19 (2020Q3-2021Q3), caracterizado pela atuação simultaneamente ativa das autoridades fiscal e monetária. Análises de robustez indicam que a identificação de regimes fiscais e explosivos é resiliente a diferentes técnicas de filtragem, enquanto a dominância monetária mostra-se mais sensível a pressupostos de modelagem. Os achados sugerem um retorno à dominância fiscal no período mais recente.

Palavras-chave: Mudança de Regime; DSGE; Dominância Fiscal; Dominância Monetária; Aprendizado de Máquina.

Contents

1 Introduction

The seminal work of Sargent and Wallace (1981) was pioneering in demonstrating that coordination between fiscal and monetary policies constitutes the most appropriate scenario for conducting sound economic policy. Until then, the *mainstream* of the time believed that inflation was an exclusively monetary phenomenon. Thus, a contractionary monetary shock would be sufficient to bring high inflation back to target. This interpretation seems intuitive: a negative monetary shock (through an increase in the interest rate) raises the cost of credit, which implies lower consumption and investment and, in turn, a lower level of output. With weaker demand, the price level would tend to fall.

However, the major issue with this approach is that it assumes a passive fiscal policy in the face of an active monetary policy, that is, a monetary dominance (MD) regime. In contrast, under a fiscal dominance (FD) regime, characterized by an active fiscal policy and a passive monetary policy, as defined by Leeper (1991), an increase in the policy interest rate will ultimately lead to higher inflation. This occurs because higher interest rates also raise the cost of rolling over public debt. This is one of the central results of the Fiscal Theory of the Price Level (FTPL), which posits that the government must stabilize debt through the continuous generation of primary surpluses or, alternatively, by resorting to inflationary financing.

The FTPL framework also suggests that, in the presence of long-term debt and under FD, the Central Bank may succeed in controlling inflation in the short run. However, as demonstrated by Cochrane (2021), in the long run investors tend to liquidate government bonds once it becomes evident that the government is unable to generate sustained primary surpluses. This liquidation generates a wealth effect, leading to a higher price level.

In the Brazilian context, this debate proves to be highly relevant, as the country has faced several episodes of economic instability due to shifts in policy conduct. The Brazilian economy has gone through distinct phases: from the consolidation of the Macroeconomic Tripod, through the interventionist turn during the era of the New Economic Matrix, to the credibility gains achieved with the implementation of the Expenditure Ceiling, and finally to a potential new rupture with the pandemic crisis and the introduction of the New Fiscal Framework. The volatility in the conduct of economic policy makes Brazil both a challenging and an ideal laboratory for classifying regimes of policy dominance.

The main objective of this dissertation is to empirically identify the periods in which the Brazilian economy was under fiscal dominance and under monetary dominance, through a hybrid methodology that combines a regime-switching DSGE model with machine learning techniques. Several studies have already addressed this topic using vector autoregressive (VAR) models and related approaches, supported by impulse–response functions to detect patterns that characterize an MD or FD regime.[1] The main limitation of this literature is that, especially when dealing with policy interactions, there is no guarantee that all relationships are strictly linear. Moreover, given the possibility that the policy regime is not static but may alternate over time, approaches that incorporate this feature, such as Markov-switching (MS) models, become particularly suitable for this type of analysis, as shown in Mendonça, Moreira and Sachsida (2017), Scaramuzzi and Muiñhos (2024), Fialho and Portugal (2005a), Teixeira (2019), and Nobrega, Maia and Besarria (2020b).

Unlike the aforementioned literature, this dissertation employs an innovative two-step hybrid strategy to classify fiscal and monetary dominance regimes.[2] In the first step, a structural DSGE model with Markovian transitions is used as a data-generating process, in which MD and FD regimes are known ex ante. Specifically, we employ the MS-DSGE model, which extends the canonical New Keynesian framework of Galí (2015) by incorporating a fiscal block inspired by the FTPL and a Markovian transition matrix. In the second step, the simulated data are used to train machine learning algorithms, which are subsequently applied to classify regimes in real time series.

The advantages of the empirical strategy adopted here can be summarized as follows: (i) there are no limitations regarding the length of time series, which is particularly convenient when analyzing peripheral economies such as Brazil, where data availability is scarce; (ii) VAR models are reduced-form representations and often rely on external identifying restrictions, whereas DSGE models are structurally grounded in economic theory, which provides discipline

[1] See, for instance, Gadelha and Divino (2008), Blanchard (2004), Zaparolli and Fernandes (2024), Tanner and Ramos (2003), Ázara (2006), Fialho and Portugal (2005a), Pastore (2014), Souza and Dias (2016), Araújo and Besarria (2014), Mendonça, Moreira and Sachsida (2017), Scaramuzzi and Muiñhos (2024), Ferreira (2015), Ornellas and Portugal (2011), Teixeira (2019), Maka (2013), Nobrega, Maia and Besarria (2020a) and Fibra and Samôa (2023).

[2] This strategy is proposed by Hinterlang and Hollmayr (2022) and applied to the United States.

for parameter interpretation and regime design, although they are also subject to specification and identification challenges; (iii) regime classification through machine learning is inherently data-driven.

In this study, the following machine learning algorithms are employed for regime classification: *Random Forest*, *Support Vector Machine* (SVM), XGBoost, and *K-Nearest Neighbors* (KNN). Among these algorithms, the results indicate that XGBoost delivers the best performance according to the evaluation metrics.

The results indicate that the XGBoost algorithm delivers superior performance in regime classification, achieving an accuracy of 95%. When applied to Brazilian data, the model uncovers a dynamic regime chronology. The economy is classified as operating under fiscal dominance between 2013 and the second quarter of 2015, followed by a transition to a monetary dominance regime between 2015 and 2017. After a subsequent return to fiscal dominance, the results identify a distinct explosive regime during the pandemic period (2020Q3 to 2021Q3), characterized by the simultaneous and active intervention of both fiscal and monetary authorities. Finally, the findings suggest a reversion to fiscal dominance from late 2021 onward, a configuration that persists through the most recent observations in 2025.

It is important to emphasize that the objective of this study is not to provide a definitive classification of fiscal–monetary policy interaction regimes in the Brazilian economy. Rather, the main purpose is to introduce a promising methodological approach that can be incorporated into the macroeconomist's toolkit as a complementary instrument for policy analysis. Accordingly, the results should be interpreted as empirical evidence conditional on the adopted methodological choices, rather than as a unique or immutable characterization of policy regimes in Brazil.

In addition to this introduction, this dissertation is organized into six subsequent sections. Section 2 provides an overview of Brazil's economic history between 2000 and 2024. Section 3 presents the theoretical foundations that motivate the analysis. Section 4 describes the theoretical model used as the data-generating process. Section 5 details the methodology employed in the empirical analysis. Section 6 presents the results and discusses them in relation to the existing literature. Finally, Section 7 offers concluding remarks.

2 A Brief History of Fiscal and Monetary Policy Conflicts in Brazil

It is not an exaggeration to state that the Central Bank of Brazil (BCB), founded in 1964, only began to operate effectively as a monetary authority in 1994 with the advent of the Real Plan. Until then, there was no clear distinction in its functions, nor was there coordination between monetary and fiscal policies. This subject is widely studied in Brazilian economic history[3]. This section aims to provide a brief historical review of Brazilian economic policy from 2000–2024.

2.1 The Success of the Real Plan and the Confidence Crisis of the Early 2000s

Among the several unsuccessful attempts to stabilize inflation in the late 1980s and early 1990s, the Real Plan stood out as the most successful. Its central achievement was the eradication of hyperinflation. Prior to its implementation, Brazil could be characterized as experiencing a classic case of fiscal dominance, in the sense proposed by Sargent and Wallace (1981), in which the government, despite its fiscal irresponsibility, managed to keep deficits at moderately low levels by resorting to seigniorage as a mechanism for debt stabilization.

From the perspective of the Fiscal Theory of the Price Level (FTPL), Loyo (1999) provides a fiscalist interpretation of Brazilian hyperinflation, highlighting the wealth effect that emerged once the monetary authority raised the policy interest rate. Nevertheless, there is little doubt that persistently high deficits, coupled with widespread indexation and a constrained monetary authority, ultimately culminated in the inflationary crisis of the early 1990s.

The Real Plan was implemented in February 1994 and, according to Barbosa (2021), its implementation can be summarized in three main steps: (i) a monetary reform based on the ideas of Arida and Resende (1986); (ii) a fiscal reform aimed at eliminating seigniorage financing, which ultimately led to the introduction of primary surplus targets in 1998; and (iii) the adoption of a monetary anchor, which helped sustain the credibility of the new currency, but at the cost of maintaining high interest rates to preserve the 1:1 parity

[3] Pastore (2024), Pastore (2021), Giambiagi et al. (2016)

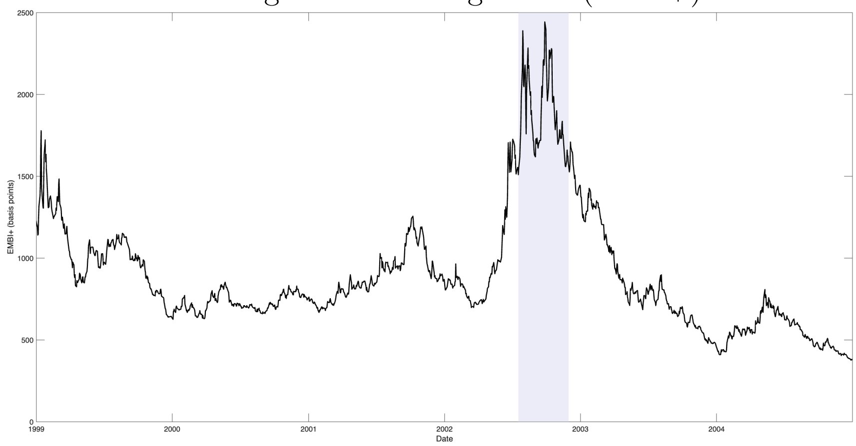
under a fixed exchange rate regime (initially).

The success of the plan was such that, while in June 1994 monthly inflation measured by the Broad Consumer Price Index (IPCA) stood at 47.43%, by the end of July it had fallen to 6.84%. Since then, Brazil has never again experienced double-digit inflation on a monthly basis.

The implementation of the Real Plan spanned roughly five years, being completed in June 1999 with the adoption of the so-called macroeconomic tripod, whose pillars are a floating exchange rate, inflation targeting, and primary surplus targets.

The first major stress test of the new regime came with the 2002 presidential elections. The administration of Fernando Henrique Cardoso had introduced significant institutional reforms, most notably the Fiscal Responsibility Law, which limited the borrowing capacity of federal, state, and municipal governments. However, the electoral lead of Luiz Inácio Lula da Silva (Lula) fueled fears of a potential default on Brazil's external debt and the dismantling of the macroeconomic tripod. The figure below shows the Emerging Markets Bond Index Plus (EMBI+), a common proxy for sovereign risk.

Figure 1: Sovereign Risk (Embi+)



Source: Data from JPMorgan
Note: Highlighted area shows the 2002 elections

The context of uncertainty drew the attention of several researchers, among them Blanchard (2004), who argued that Brazil was experiencing a new type of fiscal dominance. In this framework, whenever the Central Bank responded to an inflationary surge by raising the policy interest rate, it increased the probability of debt default, which in turn depreciated the exchange rate and further fueled inflation. However, this thesis has faced several criticisms.[4]

With the new government reaffirming its commitment to the pre-established institutional framework, and the Central Bank of Brazil responding with an interest rate hike that pushed the Selic to around 26%, the wave of capital outflows came to an end.

2.2 The New Economic Matrix

According to Pastore (2021), the successful anchoring of inflation expectations, due to the actions of the Central Bank of Brazil in 2002–2003, together with the primary surpluses generated in previous years, enabled the implementation of countercyclical policies to prevent the contagion of the 2007–2008 housing crisis. This period was characterized by a strong expansion of credit and by the prominent role of public banks, such as the National Bank for Economic and Social Development (BNDES).

In January 2007, on the eve of the global financial crisis, the Brazilian government signaled a “turn” in fiscal policy with the launch of the Growth Acceleration Program (PAC), aimed at channeling federal resources into infrastructure investment. In July 2008, faced with mounting inflationary pressures, the Central Bank of Brazil initiated a new cycle of interest rate hikes that lasted until February 2009, while the government was already preparing for the following year’s elections.

The excessive use of fiscal stimulus led to a new inflationary surge that became fully evident in 2011, under the administration of the newly elected Dilma Rousseff. In December of that same year, an episode marked the turning point of Brazilian economic policy, when the Monetary Policy Committee interrupted the ongoing cycle of interest rate hikes and unexpectedly cut the policy rate by 25 basis points, citing the risk of contagion from the “second round of the housing crisis,” which was then affecting European countries. This decision consolidated the so-called “New Economic Matrix,” a set of heterodox measures adopted by the new government, which included, among other things, expansionary fiscal and monetary policies, exchange rate depreciation, and even price controls.

In May 2013, the Monetary Policy Committee (Copom) initiated a new

[4]See, for instance, Ázara (2006), Fialho and Portugal (2005b), Pastore (2014), Gadelha and Divino (2008), Fibra and Samôa (2023).

cycle of Selic rate hikes aimed at curbing inflation expectations; nevertheless, fiscal policy remained expansionary. These efforts proved insufficient, as Barbosa (2021) shows, since between 2014 and 2015 the real interest rate remained below the natural rate of interest.

In 2014, President Dilma Rousseff was re-elected for a second term. However, in that same year, according to the Business Cycle Dating Committee (CODACE) (2023), the so-called "Great Brazilian Recession" began, resulting in a cumulative GDP contraction of 8.1% between 2014 and 2016. In 2015, the government abandoned the New Economic Matrix (NME) and attempted a return to fiscal austerity by appointing Joaquim Levy, an orthodox-oriented economist, as Minister of Finance. Nevertheless, Levy was unable to reverse the fiscal trajectory and remained in office for less than a year.

The peak of the economic and political crisis was the impeachment of Dilma Rousseff on August 31, 2016. Fiscal responsibility and the credibility of the Central Bank would only be restored under the agenda of the interim government of Michel Temer.

2.3 Temer, Bolsonaro, and Brazil's Pandemic Emergency

The Temer administration reintroduced fiscal discipline in Brazil. In its first year, the government adopted the expenditure ceiling, a fiscal rule that froze federal spending across the three branches of government for 20 years, adjusting only for past inflation. As noted by Pastore (2024), the reestablishment of fiscal discipline contributed to a decline in the natural interest rate, which in turn enabled a sustained easing cycle of the Selic rate. This process extended into the early years of the Bolsonaro administration, elected in 2018. By the end of 2019, the Selic had fallen to 5% per annum, down from 14.5% when Rousseff left office.

The outbreak of the COVID-19 pandemic in 2020 prompted governments worldwide to adopt extraordinary emergency measures. In Brazil, the Central Bank continued its cycle of monetary easing, bringing the Selic to a historical low of 2%. On the fiscal side, the federal government deployed more than R$450 billion in direct transfer programs aimed at protecting vulnerable households. In parallel, an important institutional reform was enacted in 2021, granting the Central Bank formal independence. That same year, faced with mounting inflationary pressures, the monetary authority reversed course and initiated a tightening cycle, eventually raising the Selic to 13.75% by August 2022. The Monetary Policy Committee (Copom) repeatedly underscored its concerns regarding fiscal stimulus and its potential implications for inflation dynamics.

2.4 Lula III: Under a New Fiscal Rule

The biennium of Lula's third administration has been marked by an intensification of the conflict between monetary and fiscal policies. The first year of the mandate was dominated by debates surrounding the new Fiscal Framework and its effectiveness as a credible anchor for fiscal policy.

On the monetary side, the Central Bank's Monetary Policy Committee (Copom) maintained the Selic rate at 13.25% until August 2023, when a short easing cycle began. This cycle ended in May 2024, with the policy rate reduced to 10.50%. However, in September of the same year, monetary policy turned contractionary once again, as the Central Bank initiated a new tightening cycle.

Copom's concerns during this period were centered on:

1. the resilience of the labor market;
2. the de-anchoring of inflation expectations;
3. fiscal credibility and market perceptions of fiscal policy;
4. the potential inflationary impact of exchange rate depreciation in a turbulent global environment.

The Fiscal Framework came into force in August 2023, replacing the previous expenditure ceiling. According to Secretaria do Tesouro Nacional (2023), its main features can be summarized as follows:

- The growth of federal spending is capped at 70% of the variation in primary revenues over the previous 12 months;
- If the fiscal target is not met, the following year the rule becomes stricter, limiting expenditure growth to 50% of revenue growth;
- The rule introduces a band system, constraining the real growth of primary expenditures within a floor of 0.6% and a ceiling of 2.5% per year,

thus incorporating a countercyclical mechanism. Constitutionally mandated expenditures, such as FUNDEB and the nursing wage floor, are exempt from these limits.

As highlighted by Hartung and Carvalho (2024), one of the framework's critical weaknesses lies in the mismatch between the aggregate spending cap and the rules governing mandatory expenditures, such as benefits linked to the minimum wage and earmarked health and education spending, which often grow faster than the established limit. This structural rigidity reduces the fiscal space for discretionary expenditures.

Monte Carlo simulations presented by the authors suggest that the framework delivers only a gradual improvement in the primary balance. Even if sustained over a long horizon, it is unlikely to ensure debt stabilization within the next decade.

Taken together, the historical trajectory from 2000 to 2024 underscores the persistent tension between an activist monetary policy aimed at controlling inflation and a fiscal policy that also tends to be expansionary. The dispute over which policy provides the effective nominal anchor in a context of high public debt reignites the debate on fiscal versus monetary dominance, making the Brazilian case an instructive laboratory for the objectives of this study.

3 Literature Review

This section presents the literature review. The first subsection provides a brief historical overview of the debate on policy interaction regimes, starting with the seminal contribution of Sargent and Wallace (1981) and extending to the Fiscal Theory of the Price Level. The second subsection reviews the empirical literature focused on the Brazilian economy. Finally, the fourth and last subsection surveys the recent literature on the integration of machine learning techniques with DSGE models.

3.1 The interactions between fiscal and monetary policy

Sargent and Wallace (1981) were the first to articulate the notion of dominance of one policy instrument over another. They argued that, under a fiscal dominance regime, the central bank behaves passively, allowing public debt to be monetized through seigniorage revenues. On the other hand, under a monetary dominance regime, the central bank is free to pursue disinflation through monetary contraction, while the fiscal authority acts passively, generating primary surpluses to ensure that the debt trajectory remains sustainable. With this "unpleasant arithmetic," the authors challenged the monetarist mainstream by arguing that monetary control of inflation represents only a special case of their framework.

At the core of the discussion lies the idea that the coordination between fiscal and monetary policies is preferable to a lack of coordination. No less important than the quantitative or structural analysis is the historical evidence. Sargent (1982), analyzing four episodes of hyperinflation, demonstrates that, in general, regaining control over the price level required coordinated action between monetary and fiscal authorities. In all cases, monetary contractions were accompanied by fiscal tightening, with the aim of anchoring expectations.

Leeper (1991) formalized, through a mathematical model, the central ideas proposed by Sargent and Wallace (1981), in what became known as Leeper's taxonomy. In this taxonomy, there are cases in which each policy may act either passively or actively, whether simultaneously or not. When both policies act either passively or actively, the economy falls into an explosive or indeterminate region of the taxonomy. Leeper's taxonomy has made it possible to analyze the regime of interaction between policy instruments through the lens of DSGE models. His work laid the foundations for what later became known as the Fiscal Theory of the Price Level (FTPL).

According to the FTPL, the fiscal authority plays a crucial role in the determination of the price level. Within this framework, inflation is no longer a purely monetary phenomenon, but also a fiscal one. This stands in direct contrast to the postulates of the Quantitative Theory of Money (QTM). Several authors have, at some point, advocated in favor of the FTPL, including Sims (1980), Woodford (1995), and Cochrane (2001).

The central idea of the FTPL can be summarized by the debt valuation equation, expressed as follows:

$$\frac{B_{t-1}}{P_t} = \mathbb{E}_t \sum_{k=0}^{\infty} m_{t,t+k} \cdot s_{t+k} \tag{1}$$

where $\frac{B_{t-1}}{P_t}$ denotes the real value of outstanding government liabilities in period t, $m_{t,t+k}$ is the real stochastic discount factor from period t to $t+k$, and s_{t+k} represents the expected future real primary surplus. This relationship embodies the fundamental identity of the FTPL. Intuitively, if the government fails to generate primary surpluses consistent with debt stabilization, the equilibrium adjustment must occur through the price level. In such circumstances, an increase in nominal debt unbacked by future surpluses induces agents to reallocate their portfolios away from government securities, thereby generating upward pressure on prices.

3.2 Empirical Evidence from Brazil

Due to the inherently unobservable nature of policy interaction regimes, there is no consensus on which regime predominates in the Brazilian economy. As shown in Table 1, the same year may receive different classifications across studies. This occurs because the identification of fiscal or monetary dominance is highly sensitive to the methodology employed and, in particular, to the underlying theoretical framework.

For instance, according to the definition of fiscal dominance proposed by Blanchard (2004), fiscal dominance arises when the central bank loses control over inflation outcomes in the sense that an active fiscal policy, combined with an active monetary policy, increases the probability of sovereign default and, consequently, leads to exchange rate depreciation and higher price levels. In contrast, studies that rely primarily on Sargent and Wallace (1981) or the FTPL as their theoretical foundation tend to focus on domestic variables.

The divergence in regime classifications becomes more evident when we plot a timeline of the empirical studies and their respective classifications over time, as shown in Figure 2.

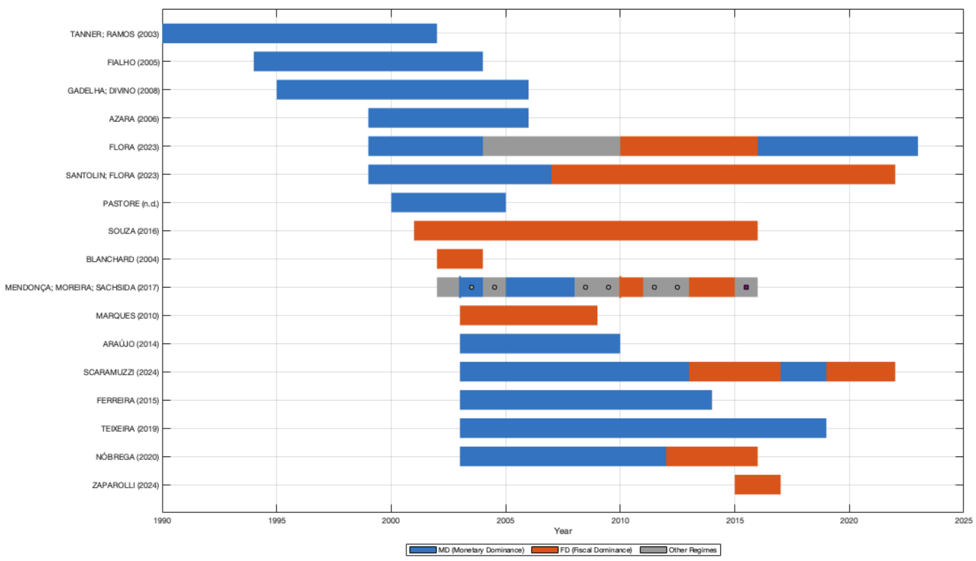
Nevertheless, when adopting a majority-vote criterion, there is a tendency to classify the period from 2000 to 2010 as one of monetary dominance, whereas the period associated with the New Macroeconomic Matrix (NMM) is frequently classified as a phase of fiscal dominance. An important exception is Mendonça, Moreira and Sachsida (2017), which departs from a dichotomous classification and instead adopts the full taxonomy proposed by Leeper (1991), identifying 2015 as a year in which both fiscal and monetary policies were simultaneously active. Empirical evidence for the post-pandemic period remains scarce; however, recent studies such as Scaramuzzi and Muiñhos (2024) and

Table 1: Classification of Brazilian macroeconomic regimes according to the literature

Paper	Methodology	Sample Period	Diagnosis
Gadelha and Divino (2008)	Granger Causality	1995–2005	MD
Blanchard (2004)	OLS and AR(1)	2002–2003	FD
Zaparolli and Fernandes (2024)	OLS and AR(1)	2015–2016	FD
Tanner and Ramos (2003)	VAR	1990–2001	MD
Ázara (2006)	OLS and AR(1)	1999–2005	MD
Fialho and Portugal (2005b)	MS-VAR	1994–2003	MD
Marques Jr (2010)	OLS and AR(1)	2003–2008	FD
Pastore (2014)	VAR	2000–2004	MD
Souza and Dias (2016)	VEC	2001–2015	FD
Araújo and Besarria (2014)	VEC	2003–2009	MD
Mendonça, Moreira and Sachsida (2017)	Markov Switching	2002–2015	FD: 2010, 2013, 2014; MD: 2003, 2005–2007
Scaramuzzi and Muiñhos (2024)	MS-VAR	2003–2021	FD: 2013–2016, 2019–2021; MD: 2003–2013, 2016–2019
Ferreira (2015)	SVAR	2003–2013	MD
Teixeira (2019)	MS-DSGE	2003–2018	MD
Nobrega, Maia and Besarria (2020a)	MS-VAR	2003–2015	MD: 2003–2011; FD: 2012–2015
Flora and Santolin (2023a)	Local Projections (LP)	1999–2022	FD: 2010–2015; MD: 1999–2003, 2016–2022
Santolin and Flora (2023)	GMM/NLS	1999–2021	MD: 1999–2006; FD: 2007–2021

Source: Author's elaboration.

Figure 2: Timeline of the empirical literature on policy interaction regimes in Brazil



Source: Author's elaboration.

Santolin and Flora (2023) find evidence consistent with fiscal dominance in the most recent period.

Although VAR-based models dominate the empirical literature on policy interaction regimes in Brazil, their reduced-form nature limits structural interpretation and regime discipline. This motivates the use of a Markov-Switching DSGE model combined with supervised machine learning, which embeds regime changes within a structural framework while extending the empirical classification of regimes beyond traditional VAR approaches.

The next subsection examines the contexts in which the integration of structural DSGE models and machine learning techniques has been adopted.

3.3 Combining DSGE Models with Machine Learning

Although still emerging, the integration of structural models and machine learning–based classification has gained momentum in recent years. A seminal contribution in this literature is Hinterlang and Hollmayr (2022), who proposes a binary classification of fiscal and monetary dominance regimes for the United States using machine learning algorithms trained on synthetic data generated by a structural model. Their results indicate that tree-based classifiers outperform alternative approaches.

Stempel and Zahner (2024) employ neural networks within a New Keynesian framework to recover the inflation weight implicit in the European Central Bank's (ECB) policy rule across member countries of the monetary union. Their results indicate that the ECB assigns a disproportionate weight to countries with more volatile inflation rates, despite these countries accounting for a relatively small share of aggregate economic activity in the euro area.

The integration of DSGE models and machine learning can also be employed for forecasting macroeconomic aggregates, particularly as a means to overcome data scarcity, as suggested by Sofianos et al. (2025). The authors use a DSGE model to generate synthetic data for France with the purpose of forecasting the trajectory of public debt. Their results show that the XGBoost algorithm performs particularly well in handling the complexity and nonlinearities present in real-world macroeconomic data.

Taken together, these contributions illustrate the potential of combining DSGE models with machine learning techniques to address identification, classification, and forecasting challenges that are difficult to tackle using traditional macroeconometric methods.

4 Theoretical Model

In this section, we develop a New Keynesian model in the spirit of Galí (2015), augmented with an explicit fiscal block following Cochrane (2021). The interaction between monetary and fiscal policy is modeled through an exogenous Markov-switching framework, allowing key policy parameters to vary across regimes.

The model is designed to generate simulated macroeconomic data under different policy configurations. These simulated data are subsequently used to train machine learning algorithms aimed at identifying fiscal and monetary dominance regimes in observed data.

4.1 Households

The economy is populated by a representative household that lives infinitely and maximizes expected lifetime utility:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, N_t), \tag{2}$$

where $\beta \in (0,1)$ is the intertemporal discount factor, C_t denotes consumption, and N_t represents hours worked. Preferences are assumed to take the constant-relative-risk-aversion (CRRA) form:

$$U(C_t, N_t) = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi}, \tag{3}$$

where σ is the inverse of the intertemporal elasticity of substitution and φ is the inverse of the Frisch elasticity of labor supply.

Consumption is defined as a Dixit–Stiglitz aggregate:

$$C_t \equiv \left(\int_0^1 C_t(i)^{1-\frac{1}{\varepsilon}}\, di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{4}$$

where $\varepsilon > 1$ denotes the elasticity of substitution across differentiated goods.

The household faces the following nominal budget constraint:

$$P_t C_t + Q_t B_t \leq B_{t-1} + W_t N_t + D_t - T_t, \tag{5}$$

where P_t is the aggregate price index, Q_t denotes the price of a one-period nominal bond, B_t represents bond holdings, W_t is the nominal wage, N_t denotes labor supply, D_t denotes dividends (firm profits) distributed to households, and T_t denotes lump-sum taxes.

The first-order conditions associated with the household's problem are given by:

$$\frac{W_t}{P_t} = C_t^{\sigma} N_t^{\varphi}, \tag{6}$$

$$Q_t = \beta E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \frac{P_t}{P_{t+1}} \right], \tag{7}$$

where Equation (6) equates the real wage to the marginal rate of substitution between consumption and leisure, and Equation (7) is the Euler equation governing intertemporal consumption choices.

4.2 Firms

A continuum of monopolistically competitive firms indexed by $i \in [0, 1]$ produces differentiated goods using the technology:

$$Y_t(i) = A_t N_t(i)^{\alpha}, \tag{8}$$

where A_t is an exogenous aggregate productivity process, and $\alpha \in (0, 1)$ represents the degree of diminishing returns to labor.

Demand for each variety is given by:

$$C_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\varepsilon} C_t. \tag{9}$$

Nominal rigidities are introduced following the Calvo Calvo (1983) pricing mechanism. In each period, firms are allowed to reoptimize prices with probability $(1 - \theta)$, while with probability θ prices remain unchanged.

4.3 Aggregate Price Dynamics

Aggregate inflation evolves according to:

$$\Pi_t^{1-\varepsilon} = \theta + (1-\theta)\left(\frac{P_t^*}{P_{t-1}}\right)^{1-\varepsilon}, \tag{10}$$

where $\Pi_t \equiv P_t/P_{t-1}$ denotes gross inflation and P_t^* is the optimal reset price chosen by firms that reoptimize in period t. In the steady state, inflation is normalized to zero, implying $\Pi = 1$.

4.4 Optimal Price Setting

Firms that are allowed to reset prices in period t choose P_t^* to maximize the expected present value of profits:

$$\max_{P_t^*} \sum_{k=0}^{\infty} \theta^k E_t \left\{ Q_{t,t+k} \left(P_t^* Y_{t+k|t} - \Psi_{t+k}(Y_{t+k|t}) \right) \right\}, \tag{11}$$

subject to the demand schedule:

$$Y_{t+k|t} = \left(\frac{P_t^*}{P_{t+k}}\right)^{-\varepsilon} C_{t+k}, \tag{12}$$

where $Q_{t,t+k}$ is the stochastic discount factor and $\Psi_t(\cdot)$ denotes the cost function.

The optimal pricing condition implies that firms set prices as a markup over a weighted average of current and expected future marginal costs, reflecting the forward-looking nature of price-setting under nominal rigidity.

4.5 Monetary Policy

Monetary policy is conducted according to a Taylor-type rule:

$$R_t = \frac{1}{\beta} \Pi_t^{\phi_\pi(s_t)} \left(\frac{Y_t}{\bar{Y}}\right)^{\phi_Y} \exp(\nu_t), \tag{13}$$

where R_t is the gross nominal interest rate, ν_t is a monetary policy shock following an AR(1) process, and $\phi_\pi(s_t)$ governs the monetary policy response to inflation. The parameter $\phi_\pi(s_t)$ varies according to the fiscal–monetary interaction regime (MD, FD, EX), that is, it is calibrated with different values depending on the prevailing regime [5] . This regime-switching structure is described in more detail in Subsection 4.8, which presents the Markov-switching process across regimes.

4.6 Fiscal Policy

The government issues one-period nominal bonds and satisfies the identity:

$$SP_t = T_t - G_t, \tag{14}$$

where SP_t denotes the real primary surplus.

The government budget constraint in real terms is given by:

$$\frac{B_t}{R_t} = \frac{B_{t-1}}{\Pi_t} - SP_t. \tag{15}$$

Government spending is assumed to be constant and equal to a fixed share of steady-state output:

$$G_t = g \cdot \bar{Y}. \tag{16}$$

Fiscal policy follows the rule:

$$SP_t = \rho_{sp} SP_{t-1} + (1 - \rho_{sp}) \bar{SP} \cdot \bar{Y} + \delta_B(s_t)\big(B_{t-1} - \bar{B}\big) + \delta_Y\big(Y_t - \bar{Y}\big) - f_t, \tag{17}$$

where f_t is a fiscal shock following an AR(1) process, and $\delta_B(s_t)$ is a regime-dependent parameter that takes different calibrated values across regimes according to the Markov-switching process described in Subsection 4.8.

4.7 Market Clearing

Goods market equilibrium requires:

$$Y_t = C_t + G_t. \tag{18}$$

[5]The calibrated parameter values for each regime are reported in Table A.1 in the Appendix. For instance, $\phi_\pi(s_t)$ equals 1.5 under monetary dominance, whereas under fiscal dominance monetary policy is passive and the parameter is calibrated at 0.5.

This condition states that aggregate output is fully absorbed by private consumption and government spending. Since the model abstracts from capital accumulation, investment, and external trade, total production is allocated exclusively between households and the government. As a result, fiscal policy affects aggregate demand through lump-sum taxes/the primary surplus rule and indirectly through its interaction with monetary policy and debt dynamics.

4.8 Markov-Switching

Following a Markov process, the economy can transition across three policy-interaction regimes, with transition probabilities defined exogenously[6]

Formally, the Markov chain with three regimes can be described by the following transition matrix:

$$P = \begin{bmatrix} p_{MD,MD} & p_{MD,FD} & p_{MD,EX} \\ p_{FD,MD} & p_{FD,FD} & p_{FD,EX} \\ p_{EX,MD} & p_{EX,FD} & p_{EX,EX} \end{bmatrix}, \tag{19}$$

where each element $p_{i,j}$ represents the probability of transitioning to regime i at time $t+1$, conditional on being in regime j at time t, that is,

$$p_{i,j} = \Pr(r_{t+1} = i \mid r_t = j), \quad i, j \in \{MD, FD, EX\}. \tag{20}$$

The three regimes correspond to monetary dominance (MD), fiscal dominance (FD), and an explosive regime (EX), in which both fiscal and monetary policies are simultaneously active.

Following Hinterlang and Hollmayr (2022), we define the economy as operating under monetary dominance (MD) when monetary policy reacts actively to inflation, satisfying the Taylor principle, while fiscal policy adjusts

[6] Several attempts were made to endogenize the transition matrix; however, the resulting specifications were not sufficiently robust and did not improve the training performance of the algorithms relative to data generated under fixed transition probabilities. Appendix D.1 reports an alternative exercise in which transition probabilities are modeled as functions of state variables through a logit specification. We also explored an alternative strategy that avoids the use of a Markov process by simulating data from individual policy regimes in Dynare and subsequently using these simulated series to train the classifiers. The results obtained under this approach are also reported in Appendix D.1. The use of Dynare presents two major limitations in this context: (i) it is not possible to simulate the explosive regime, since Dynare relies on local perturbation methods; and (ii) the simulated data do not embed information about transitions between regimes.

the primary surplus in order to stabilize the public debt trajectory. In this regime, the parameters are calibrated as follows:

$$\phi_\pi(s_t) = 1.5, \qquad \delta_B(s_t) = 0.5.$$

The economy is said to be under fiscal dominance (FD) when monetary policy behaves passively, reacting weakly to inflation, and fiscal policy does not systematically respond to the level of public debt. In this case, the adopted calibration is:

$$\phi_\pi(s_t) = 0.5, \qquad \delta_B(s_t) = 0.0.$$

Finally, an explosive regime (EX) is defined as a configuration in which monetary policy is active, while fiscal policy remains passive and does not adjust the primary surplus in response to public debt. This regime is characterized by the following parameter values:

$$\phi_\pi(s_t) = 1.5, \qquad \delta_B(s_t) = 0.0.$$

These three configurations define the regimes used in the Markov process and determine the labels assigned to the time series simulated by the structural model.

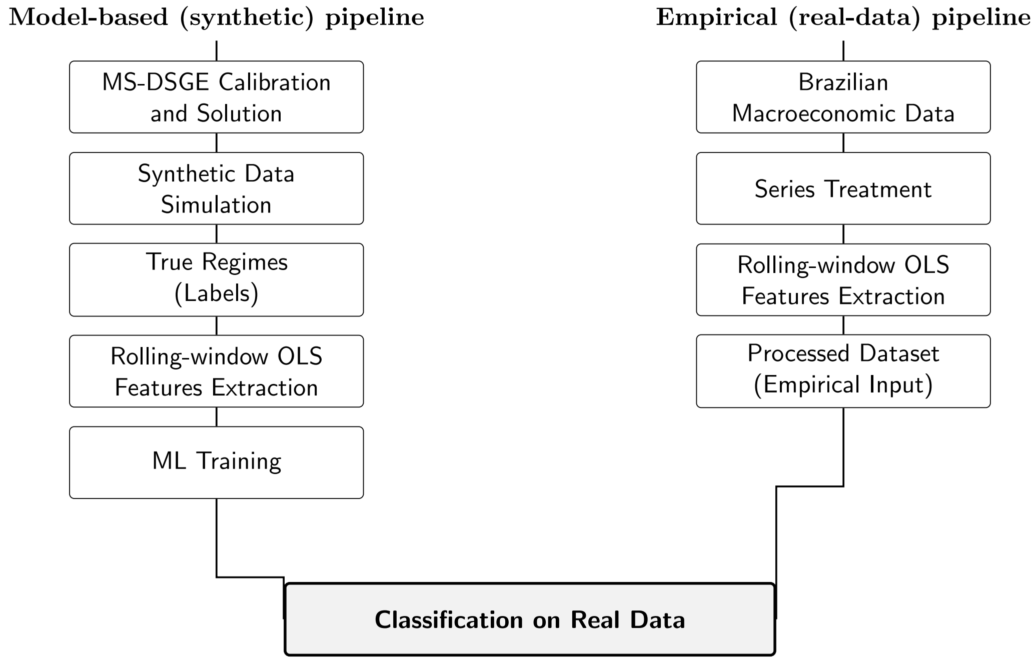
5 Methodology

This section describes in detail the methodological procedure employed in this study. The empirical strategy can be summarized as follows. First, the nonlinear MS-DSGE model is calibrated and solved numerically using the RISE Toolbox in the MATLAB environment, since traditional tools for solving DSGE models, such as Dynare, do not natively support regime-switching structures. Once the model solution is obtained, artificial time series are generated for the model variables and labeled according to each fiscal–monetary interaction regime, namely monetary dominance, fiscal dominance, and the explosive regime.

Second, real macroeconomic data are processed following the procedures described in Subsection 5.2. This step allows for the estimation of linearized versions of Equations (13) and (17) via ordinary least squares using ten-year rolling windows, yielding the time-varying policy reaction coefficients $\hat{\phi}_{\pi,t}$ and $\widehat{\delta}_{B,t}$. This rolling-window estimation is applied consistently to both simulated and real data, ensuring real-time consistency and avoiding look-ahead bias. Although these variables are unobservable by construction, they convey economically meaningful information about the prevailing interaction between fiscal and monetary policies.

Third, machine learning algorithms are trained and evaluated using the simulated data, which serve as a theory-consistent data-generating process. Performance metrics are computed for each classification model during this stage. Finally, the trained classifiers are applied to real time series, allowing for the identification and historical classification of fiscal–monetary policy regimes over time. Figure 3 summarizes the main methodological steps of the analysis.

Figure 3: Methodological flow: Integration of structural MS-DSGE simulation and ML classification.



Source: Author's elaboration.

It is important to emphasize that the machine learning classifier should not be interpreted as a structural estimator of policy rules, but rather as a pattern-recognition device trained on theoretically disciplined synthetic data.

5.1 Artificial data

As mentioned before, the MS-DSGE model is solved using the RISE toolbox[7]. From the numerical solution, we simulate artificial time series in which the number of observations in each regime depends on the underlying Markov-switching process. The simulated dataset contains a total of 10,000 observations, matching the sample size used in the exercise conducted by Hinterlang and Hollmayr (2022).

From the total number of observations, 70% are used to train the model and 30% to evaluate the effectiveness of the training, in order to compute in-sample statistics such as the model's accuracy.

The sample of the baseline model is distributed as follows: 83.37% of the observations correspond to monetary dominance (MD), 14.08% to fiscal dominance (FD), and 2.55% to the explosive regime. This data distribution is inspired by findings in the existing literature, which consistently indicate that the dominant regime is the most prevalent, the second regime occurs sporadically, and the third regime is relatively rare [8].

Although all variables in the model were simulated, the final dataset ultimately depends on the availability of real-world data. This is discussed in more detail in the next subsection.

5.2 Real data

All real-world Brazilian time series were extracted from the Time Series Management System (SGS), maintained by the Central Bank of Brazil. As mentioned in the previous subsection, the real dataset determined the structure of the simulated training dataset. This alignment is necessary to ensure that the regimes are correctly classified, as it requires matching both real and simulated data.

To ensure consistency between the simulated and real-world data, we applied several time series transformations. The seasonal components of the series were removed using the ARIMA X-13 procedure, while their trends were

[7]The model was primarily calibrated following the specialized literature. Table A.1, presented in the Appendix, reports each variable and its corresponding calibrated value.

[8]Several alternative regime distributions were explored. The configuration reported in the main text was selected because it delivers the most reliable training performance across models. Appendix D presents additional exercises, including a balanced sample one.

extracted with the Hodrick–Prescott (HP) filter, setting $\lambda = 1600$ given that the data are quarterly.

The table below summarizes the name, identifier, and data treatment applied to each series. Each time series reported in Table 2 has a corresponding simulated variable, which is incorporated as a feature in the model.

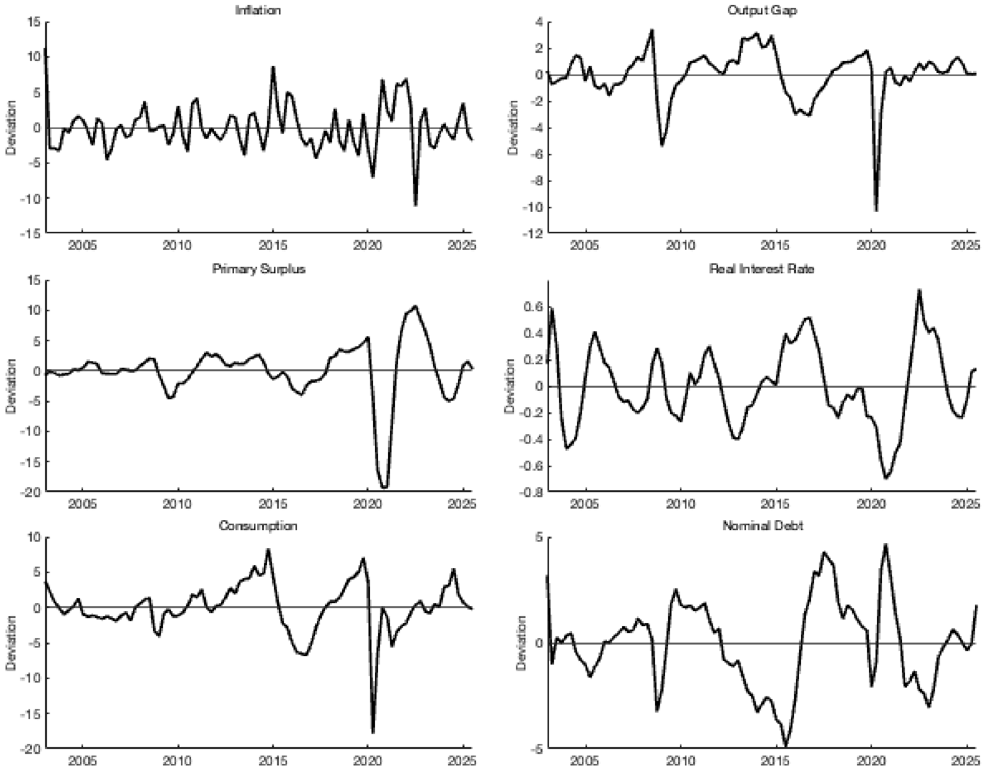
Table 2: Description, Source, and Data Treatment of Variables

Variable	**Orig. Freq.**	**SGS**	**Data Treatment**
Gross Domestic Product (GDP)	Quarterly	22099	Series in levels consolidated at the end of each quarter and seasonally adjusted using X-13 ARIMA-SEATS. Transformed into logarithms (log $\times 100$) and filtered with the Hodrick–Prescott filter ($\lambda = 1600$) to obtain the output gap.
Inflation (IPCA)	Monthly	433	Monthly IPCA inflation rates (% m/m) are first converted into a price-level index P_t defined as $P_t = P_0 \prod_{j \leq t} \left(1 + \frac{\text{IPCA}_j}{100}\right)$. The quarterly price level is taken as the end-of-quarter observation. Quarterly inflation is then computed as the annualized log change, $\pi_t = 400 \ln\left(\frac{P_t}{P_{t-1}}\right)$, that is, $\pi_t = \log(P_t/P_{t-1}) \times 100 \times 4$.
Primary Surplus (% of GDP)	Monthly	5793	Twelve-month accumulated fiscal flow converted to quarterly frequency using end-of-quarter observations. The series is multiplied by -1 when necessary so that positive values indicate fiscal expansion.
Nominal Policy Interest Rate (Selic, % p.a.)	Monthly	4189	Quarterly average obtained from monthly observations and transformed into an annualized continuous rate (log transformation) to ensure consistency with the DSGE framework.
Real Interest Rate (% p.a.)	Monthly / Quarterly	–	Constructed ex post as the difference between the quarterly annualized nominal interest rate and quarterly annualized inflation, both expressed in logarithmic terms.
Gross Government Debt (% of GDP)	Monthly	4513	Converted to quarterly frequency using simple averages of monthly observations.
Household Consumption	Quarterly	22100	Series in levels consolidated at the end of each quarter and seasonally adjusted using X-13 ARIMA-SEATS.

Source: Author's calculations based on data from the Central Bank of Brazil's Time Series Management System (SGS).

Figure 4 displays the transformed series after the treatments described in Table 2, covering the period from 2003Q1 to 2025Q3. The starting date is determined solely by data availability. Because the latent variables are computed using ten-year rolling windows, however, the regime classification is only available from 2013Q1 onward. The procedure for estimating non-observable variables via rolling-window OLS is discussed in the following subsection.

Figure 4: Real Brazilian Data



Source: Central Bank of Brazil's Time Series Management System (SGS).

5.3 Rolling-window feature construction

This subsection describes the construction of time-varying policy reaction measures used as inputs in the machine learning classifier. These features are designed to capture the evolving behavior of monetary and fiscal authorities in a manner consistent with the theoretical mechanisms underlying fiscal dominance, monetary dominance, and the regime in which both policies act actively.

Two unobservable-by-construction features are incorporated into the model: the time-varying monetary policy reaction coefficient, $\hat{\phi}_{\pi,t}$, and the time-varying fiscal response to public debt, $\widehat{\delta}_{B,t}$. These variables are obtained through rolling-window OLS estimations of linearized versions of Equations (13) and (17), respectively.[9]

$$R_t = \alpha_R + \hat{\phi}_{\pi,t}\, \pi_t + \phi_y\, y_t + \varepsilon_t^R, \tag{21}$$

[9]This implies that static versions of these equations are estimated, in the sense that their coefficients do not vary explicitly across regimes.

$$sp_t - \rho_{sp}\, sp_{t-1} = \alpha_{sp} + \widehat{\delta}_{B,t}\, B_{t-1} + \gamma_y\, y_t + \varepsilon_t^{sp}, \tag{22}$$

The first variable, $\hat{\phi}_{\pi,t}$, provides a time-varying estimate of the monetary authority's response to inflation and can be interpreted as a local approximation of the inflation coefficient in a Taylor-type rule. It is obtained from rolling regressions of the nominal interest rate on inflation and the output gap. The second variable, $\widehat{\delta}_{B,t}$, measures the fiscal authority's response to public debt and is estimated from rolling regressions of the primary surplus on its own lag, lagged public debt, and the output gap, capturing the degree of fiscal feedback or discipline over time. Although not directly observable, these variables provide economically meaningful summaries of policy behavior that help the classifier distinguish between regimes characterized by active or passive monetary and fiscal stances.

The use of estimated or latent variables as predictors is well established in the recent macroeconomic machine learning literature. Studies such as Coulombe et al. (2022), Garcia, Medeiros and Vasconcelos (2017), and Liu, Pan and Xu (2024) rely on filtered or estimated objects, including output gaps, common factors, or expectation measures, as inputs to forecasting and classification models. In practice, these variables often embed relevant cyclical information and tend to improve predictive performance.

Following Liu, Pan and Xu (2024) and Garcia, Medeiros and Vasconcelos (2017), this study adopts rolling-window estimation to accommodate the instability of macroeconomic relationships over time. Re-estimating the policy reaction coefficients over rolling samples reduces reliance on parameters estimated in distant periods that may correspond to different regimes and keeps the constructed features aligned with the most recent data dynamics. Moreover, because each rolling estimate uses only information available up to that period, the procedure is consistent with a real-time environment and avoids look-ahead bias.

In the empirical exercises, a ten-year rolling window delivered the best overall performance.[10] Shorter windows were more responsive to local changes but generated substantially noisier estimates, while longer windows produced smoother series at the cost of reduced adaptability. The ten-year specification thus represents a reasonable compromise for the Brazilian data. As a conse-

[10] Results obtained without the rolling-window procedure are reported in Section D.4 of the Appendix.

quence of this choice, the effective sample available for regime classification spans the period from 2013Q1 to 2025Q3.

5.4 Supervised Machine Learning

Supervised machine learning refers to a branch of machine learning techniques in which an algorithm is trained on a labeled dataset in order to learn from known data and predict future labels based on the training. In our case, the labeled dataset comes from the MS-DSGE simulation, where the regimes: monetary dominance (MD), fiscal dominance (FD), or explosive are known a priori. Making a connection with the standard econometric framework, our problem can be represented as a multinomial logit model, in which we aim to predict whether an observation corresponds to the MD, FD, or explosive regime, based on a set of explanatory variables such as inflation, primary surplus-to-GDP, debt-to-GDP, and the real interest rate, among others.

In the following, we provide a brief [11] overview of the classifiers. The goal is to describe how each algorithm works, highlighting their main advantages and limitations.

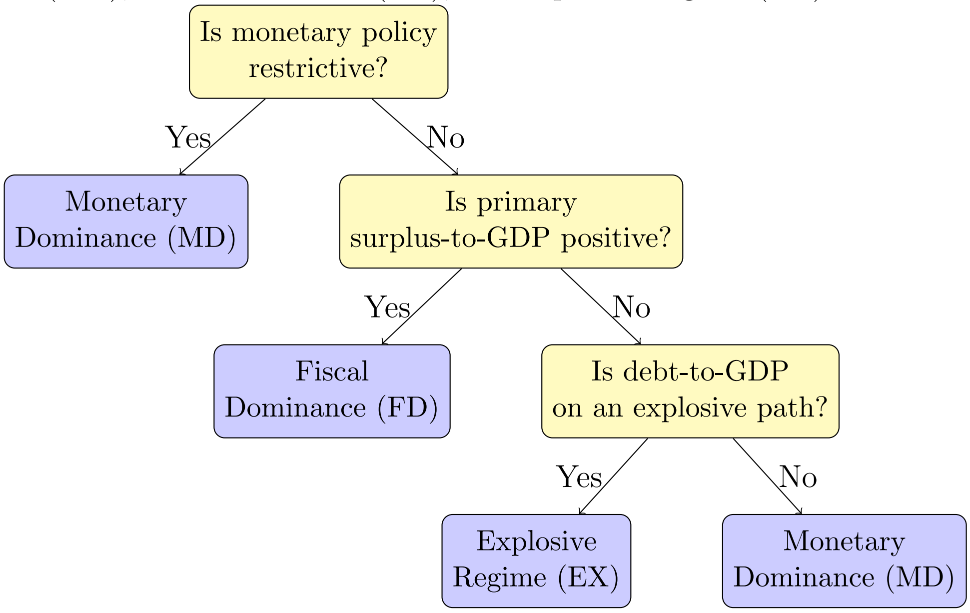
Decision Trees

The central idea of decision trees is to split the variable space into homogeneous regions through sequential decisions. At each node, one explanatory variable (feature) is tested according to a decision rule, guiding the algorithm toward the final node (the leaf), where the target class is assigned. The idea behind decision trees was originally proposed by Breiman et al. (1984). The operational mechanism of the model is illustrated in Figure 5 through a schematic example.

The main advantage of the Decision Tree model, as highlighted by Shalev-Shwartz and Ben-David (2014), lies in its high interpretability. However, these models are also prone to overfitting if their hyperparameters are not properly chosen.

[11] A more complete and formal explanation of how machine learning techniques work can be found in Shalev-Shwartz and Ben-David (2014).

Figure 5: Illustrative decision tree for regime classification: monetary dominance (MD), fiscal dominance (FD), and explosive regime (EX).



Source: Author's elaboration.

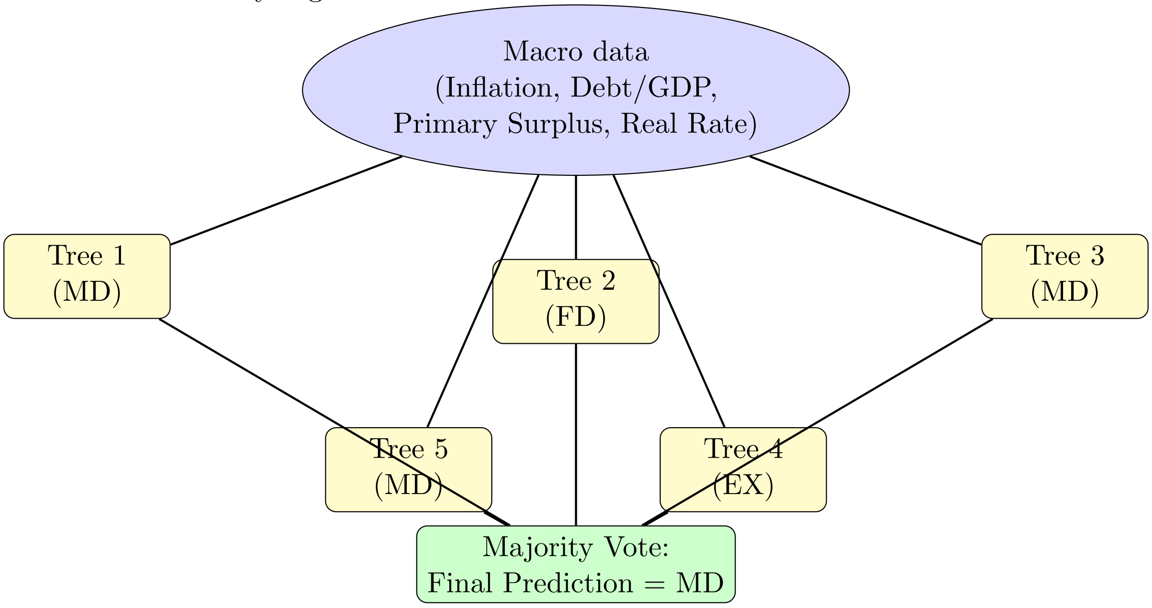
Random Forest

The Random Forest, proposed by Breiman (2001), is a natural evolution of the original Decision Tree model. It maintains a relatively high level of interpretability, however, instead of relying on a single tree to make predictions, the Random Forest combines the decisions of multiple trees, each trained on random subsets of the data. During the training process, each tree produces a prediction for the data's label. Then, following a majority voting scheme, the model determines its final output (prediction).

Since the final output is determined not by a single tree but by an entire forest, and because each tree is built on a random subset of the data, outliers may appear in some trees but are neutralized by the majority voting mechanism. As mentioned earlier, the model has a relatively high level of interpretability. This means that it is possible to identify which features contribute most to the final decision, for instance, by calculating their feature importance scores. The figure 6 summarizes how the model determines its final output.

The Random Forest belongs to a family of classifiers known as ensemble learners. This family of models starts from a weak learner (a single classifier, such as a decision tree) and builds a strong learner by combining many trees.

Figure 6: Illustration of the Random Forest applied to the classification of fiscal and monetary regimes.



Source: Author's elaboration.

Boosting methods

The boosting methods are also ensemble techniques in the sense that they start from a weak learner and build a strong one as the final output. The key difference from the tree-based methods (Decision Tree and Random Forest) lies in the fact that boosting algorithms build trees sequentially, where each tree learns from the mistakes made by the previous ones. To our pool of algorithms, we selected two boosting methods: AdaBoost and XGBoost.

AdaBoost stands for Adaptive Boosting and was originally proposed by Freund and Schapire (1997). The algorithm learns from its past mistakes by adjusting the weights of misclassified observations, allowing subsequent models to focus more on difficult cases. The difficulty criterion is established according to the performance of previous models in classifying each observation.

XGBoost stands for Extreme Gradient Boosting and was originally proposed by Chen and Guestrin (2016). This algorithm is also capable of learning from its past mistakes; however, the authors formalized boosting as an optimization problem based on a loss function. The tree parameters are chosen to minimize the gradient of the error.

There are several advantages to using XGBoost for classification tasks, such as its robustness to missing values and its ability to prevent overfitting.

The model is also highly optimized, as it employs parallelization for data processing, allowing it to handle datasets that do not fit entirely into the computer's RAM.

K-Nearest Neighbors (KNN)

The KNN is a nonparametric classification algorithm, originally proposed in the seminal work of Cover and Hart (1967). Its operation is simple: to classify a new observation, the algorithm identifies the k points in the training set that are closest to it (usually based on the Euclidean distance). The new sample is then assigned to the class that is most frequent among these k neighbors.

The main advantage of KNN is that it is nonparametric, meaning that it does not require prior assumptions about the statistical distribution of the data. However, as highlighted by Hinterlang and Hollmayr (2022), the algorithm suffers from the so-called "curse of dimensionality," which reduces its efficiency and accuracy in datasets with a high number of explanatory variables.

Support Vector Machine (SVM)

Assuming a dataset that can be perfectly separated by a line (or plane), it is natural to imagine that there are infinitely many lines that could perform this separation. According to Cortes and Vapnik (1995), the intuition behind the SVM suggests that the best line is the one that is as far as possible from both groups. In the context of this study, the algorithm finds the optimal boundary between the datasets labeled as MD, FD or explosive.

To deal with nonlinearity, as pointed out by Hinterlang and Hollmayr (2022), the SVM employs the so-called kernel trick. The algorithm does not need to explicitly compute the inner product using high-dimensional vectors. The kernel function acts as a "shortcut function" that efficiently calculates this inner product using only the vectors in the original low-dimensional space. This allows the SVM to create nonlinear decision boundaries without explicitly projecting the data into a higher-dimensional space.

SVMs are fairly robust to outliers and noise in the data. However, their performance depends crucially on the choice of hyperparameters. Other drawbacks include lower interpretability and high computational costs.

5.4.1 Evaluation Metrics of the Models

The performance metrics of the trained models are derived from the confusion matrix. After training, the model's predictions on the test set are compared with the true labels, enabling the calculation of accuracy and error proportions.

A generic confusion matrix for a multiclass classification problem, evaluated under a one-vs-rest representation for regime i, can be summarized as follows:

Table 3: Generic Confusion Matrix (One-vs-Rest Representation for Regime i)

Actual / Predicted	**Regime** i	**Not Regime** i
Regime i	True Positive (TP)	False Negative (FN)
Not Regime i	False Positive (FP)	True Negative (TN)

Source: Author's elaboration.

In this study, a true positive (TP) occurs when the model correctly assigns a case to its actual regime, while a true negative (TN) corresponds to cases in which the model correctly identifies that a given observation does not belong to a specific regime. Conversely, a false positive (FP) occurs when the model incorrectly classifies a case as belonging to a regime that it does not actually belong to, and a false negative (FN) occurs when the model fails to identify a case that truly belongs to a given regime.

Using these proportions, we derive several performance metrics that assess the trained model's effectiveness on the test data. The evaluation metrics used in this dissertation are presented in Table 2.

Table 4: Performance Metrics

Metric	Formula	Description
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Overall proportion of correctly classified cases by the model.
Precision	$\frac{TP}{TP+FP}$	Proportion of predicted positive cases that are actually positive.
Recall (Sensitivity)	$\frac{TP}{TP+FN}$	Proportion of actual positive cases that were correctly identified by the model.
F1-Score	$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$	Harmonic mean between precision and recall, balancing both metrics.
Log Loss	$-\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1-y_i)\log(1-p_i)]$	Measures the uncertainty of probabilistic classifications; lower values indicate better calibrated models.
AUC (Area Under the Curve)	—	Represents the probability that the model ranks a randomly chosen positive instance higher than a negative one; measures overall discriminatory power.

Notes: For multiclass classification problems, precision, recall, F1-score, and AUC are computed using a one-vs-rest strategy for each class and subsequently aggregated using macro-averaging.
Source: Elaborated based on James et al. (2013).

6 Results

This section presents the results of the proposed empirical exercise. The first subsection reports the in-sample training performance metrics, which are used to select the best-performing model. This model is then adopted as the benchmark for classifying fiscal–monetary regime interactions in the real data. The second subsection presents a chronological analysis of the classified policy-interaction regimes for the Brazilian economy, accompanied by a discussion of the macroeconomic policy context and comparisons with related findings in the literature. Finally, the third subsection reports a set of robustness checks assessing the stability of the results.

6.1 Training Performance Metrics

The table below reports the results of model training using simulated data. It is important to emphasize that real data do not affect model performance in terms of evaluation metrics, as they are not used during the training or validation stages.

In general, the AdaBoost and XGBoost models delivered the strongest performance after training, with both achieving an accuracy of 95%. These results point to a clear superiority of tree-based ensemble methods in this clas-

Table 5: Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score	Log Loss	AUC
KNN	0.93	0.84	0.57	0.60	0.36	0.83
AdaBoost	0.95	0.92	0.71	0.77	0.95	0.94
Decision Tree	0.93	0.84	0.57	0.60	0.36	0.83
SVM	0.93	0.64	0.57	0.59	0.25	0.86
RF	0.95	0.90	0.66	0.72	0.19	0.95
XGBoost	0.95	0.84	0.67	0.73	0.17	0.95

Source: Author's elaboration.

sification task, as such models are particularly well suited to capturing non-linear relationships and complex interactions among the simulated variables. This finding is consistent with the evidence reported in Hinterlang and Hollmayr (2022), who document the strong performance of ensemble tree-based algorithms in regime classification settings.

Although AdaBoost attains a relatively high F1-score, XGBoost was selected as the benchmark model due to its superior performance in terms of Log Loss (0.17). In the context of macroeconomic regime analysis, the quality and calibration of estimated probabilities are of central importance. The lower Log Loss achieved by XGBoost indicates a better-calibrated probabilistic output, which is particularly valuable for identifying periods of heightened uncertainty and transitions between policy regimes.

6.2 Real World Data Classification

Figure 7 displays the historical classification of fiscal–monetary policy interaction regimes over the 2013Q1–2025Q3 period, as produced by the XGBoost classifier. According to the patterns learned from the MS-DSGE simulated data, the results suggest that the Brazilian economy operated under fiscal dominance from 2013 through the second quarter of 2015. In the third quarter of 2015, the classification indicates a transition to a monetary dominance regime, which persists for approximately two years.

The classification of the 2015–2017 period as one of monetary dominance is consistent with the Central Bank's efforts to reassert control over inflation beginning in 2015, as well as with the abandonment of the New Economic Matrix in 2016. This shift was marked by the appointment of Joaquim Levy as Minister of Finance and the announcement of fiscal austerity measures. Following President Dilma Rousseff's removal in mid-2016, the interim administration explicitly committed to stabilizing the public debt trajectory, most notably through the implementation of an expenditure ceiling, which came into force in January 2017.

From the fourth quarter of 2017 to the second quarter of 2020, the model assigns higher probabilities to a fiscal dominance regime, a pattern that is also evident in Figure 8, with a brief and isolated episode of an explosive regime in the third quarter of 2017. From the third quarter of 2020 onward, the Brazilian economy enters a regime in which both fiscal and monetary policies are simultaneously active, in the sense of Leeper (1991). This configuration reflects policymakers' efforts to mitigate the economic impact of the COVID-19 pandemic.

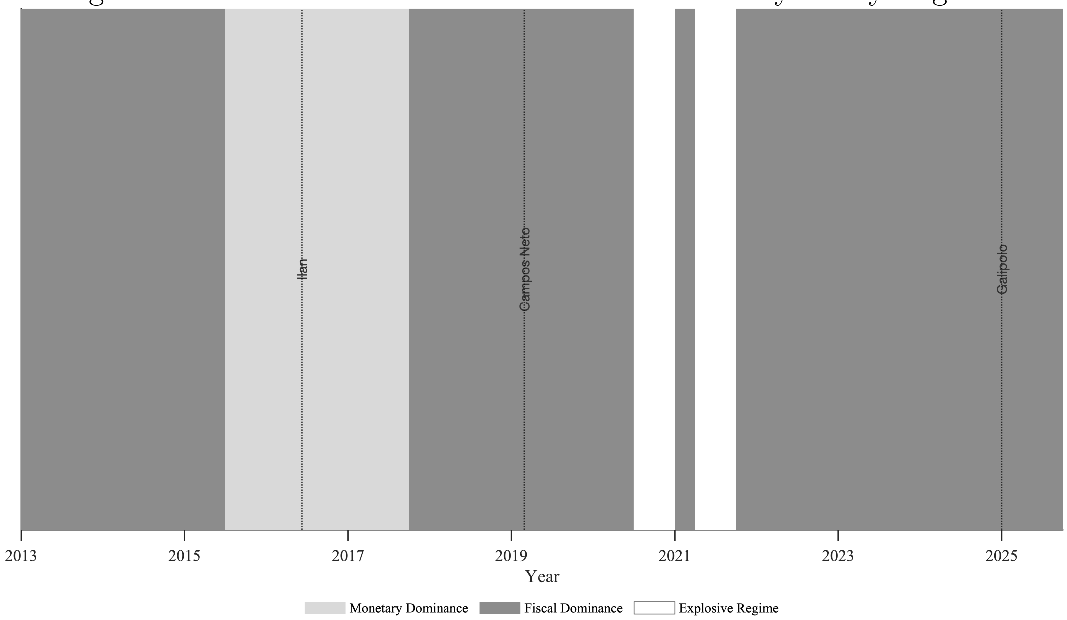
In 2021, following a sharp increase in inflation associated with the monetary and fiscal stimulus implemented in 2020, the Central Bank initiated a tightening cycle. The explosive regime ends in the third quarter of 2021, after which the economy returns to a fiscal dominance configuration, with the classifier assigning a probability of approximately 86% to fiscal dominance in the third quarter of 2025 [12].

The findings presented here are well aligned with the existing literature, particularly regarding the characterization of the Dilma Rousseff administration as a period of fiscal dominance, as documented by Santolin and Flora (2023), Flora and Santolin (2023b), Nobrega, Maia and Besarria (2020a), and Scaramuzzi and Muiñhos (2024). Notably, this body of work also provides evidence of fiscal dominance in 2019, consistent with the classification obtained in this study.

There is still a limited number of studies that attempt to classify policy regimes in the post-pandemic period. Existing contributions that analyze this phase typically restrict their frameworks to only two regimes: monetary dominance and fiscal dominance. In contrast, a key contribution of the present study is the explicit inclusion of an explosive regime, with the results indicating its presence during the pandemic period.

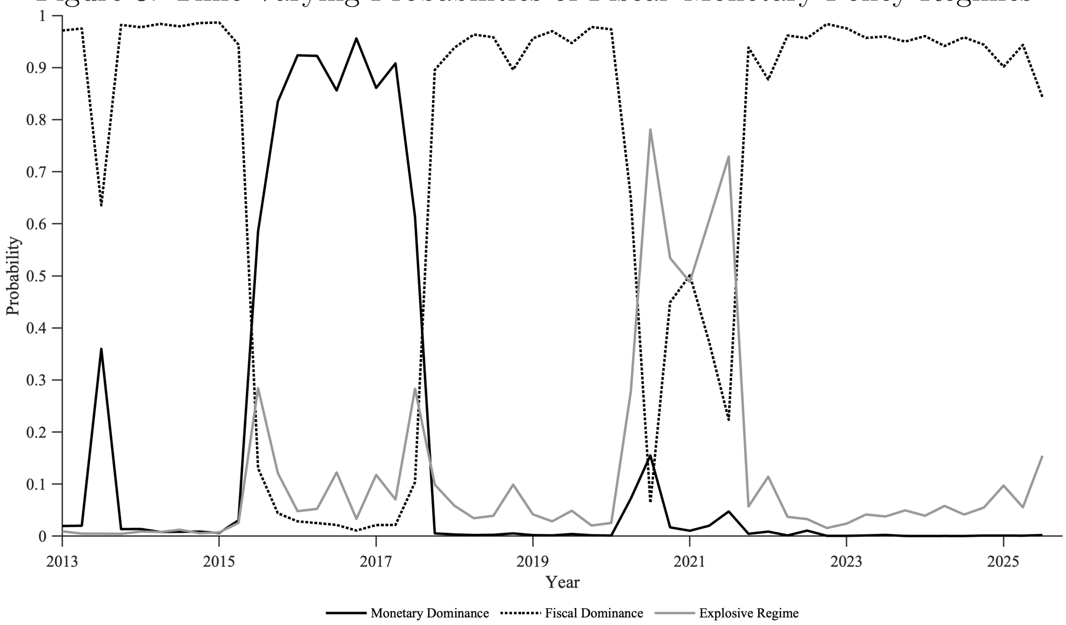
[12] Overall, the classifiers yield highly similar regime classifications, as documented in Section B.2 of the Appendix. Notably, all algorithms classify the third quarter of 2025 as fiscal dominance (FD) period. Table B.3 presents the detailed probabilities assigned to each regime for every observation classified by XGBoost.

Figure 7: Historical Classification of Fiscal–Monetary Policy Regimes



Notes: Dark gray areas indicate Fiscal Dominance, light gray areas indicate Monetary Dominance, and white areas correspond to the Explosive Regime. Dotted vertical lines mark Central Bank presidential appointment periods. Source: Author's elaboration.

Figure 8: Time-Varying Probabilities of Fiscal–Monetary Policy Regimes



Source: Author's elaboration.

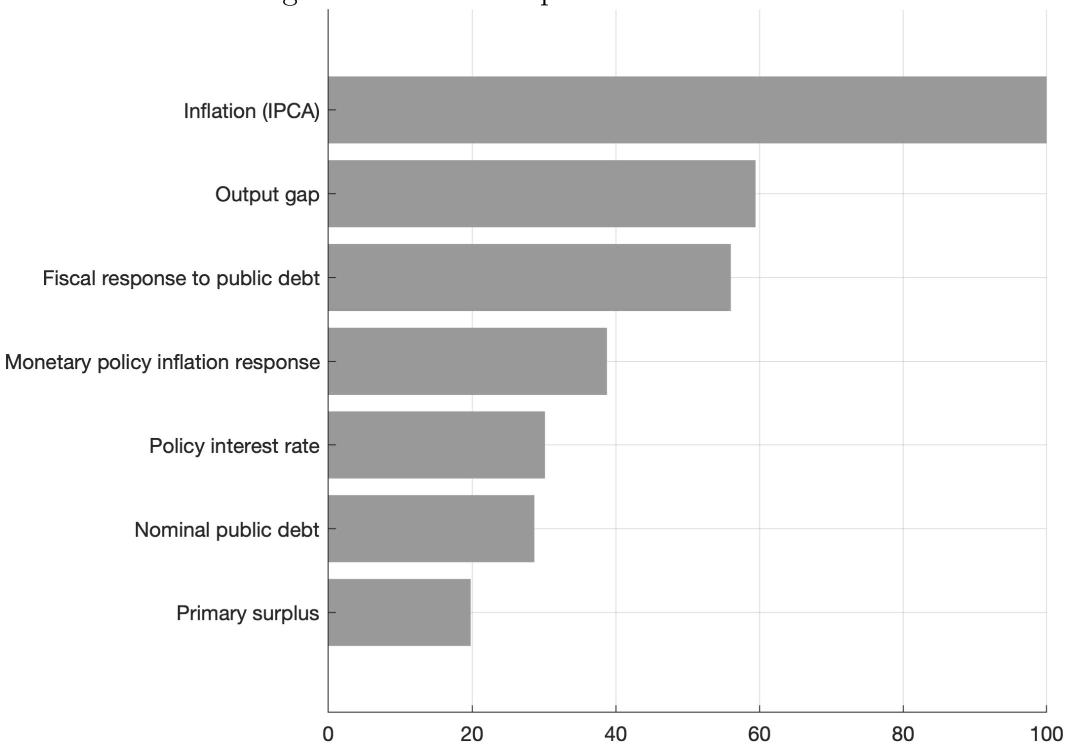
6.3 Feature Importance

This subsection examines which variables are most informative for distinguishing the policy regimes prevailing in the Brazilian economy. One way to shed light on this mechanism is through the analysis of feature importance, which provides a measure of how strongly each variable contributes to the model's classification performance. In the context of XGBoost, feature importance is derived from the role each feature plays in the construction of the decision trees that compose the ensemble.

In this study, variable importance is measured using the gain criterion, which captures the average reduction in the loss function associated with splits that rely on a given feature. Intuitively, a higher gain indicates that a variable is particularly effective in partitioning the data in a way that improves regime classification, thus carrying greater informational content about the underlying policy regime.

Figure 9 reports the relative feature importance for the XGBoost model. All measures are normalized with respect to the most important variable, allowing for a direct comparison of their relative contributions.

Figure 9: Feature Importance - XGBoost



Source: Author's elaboration.

The results indicate that inflation is by far the most informative variable for regime classification, highlighting its central role in distinguishing between monetary, fiscal, and explosive policy configurations. This finding is

[121] Feature importance was also computed for the remaining tree-based models (Random Forest and single Decision Tree). In all cases, the resulting rankings were qualitatively identical.

consistent with the evidence reported by Hinterlang and Hollmayr (2022), in which inflation also emerges as one of the most important predictors for regime classifiers.

The output gap emerges as the second most relevant feature, underscoring the importance of real economic conditions in shaping policy interactions and regime dynamics. Measures capturing the fiscal response to public debt and the monetary policy response to inflation also rank highly, reflecting the pivotal role of policy feedback rules in determining whether the economy operates under monetary dominance, fiscal dominance, or an explosive regime.

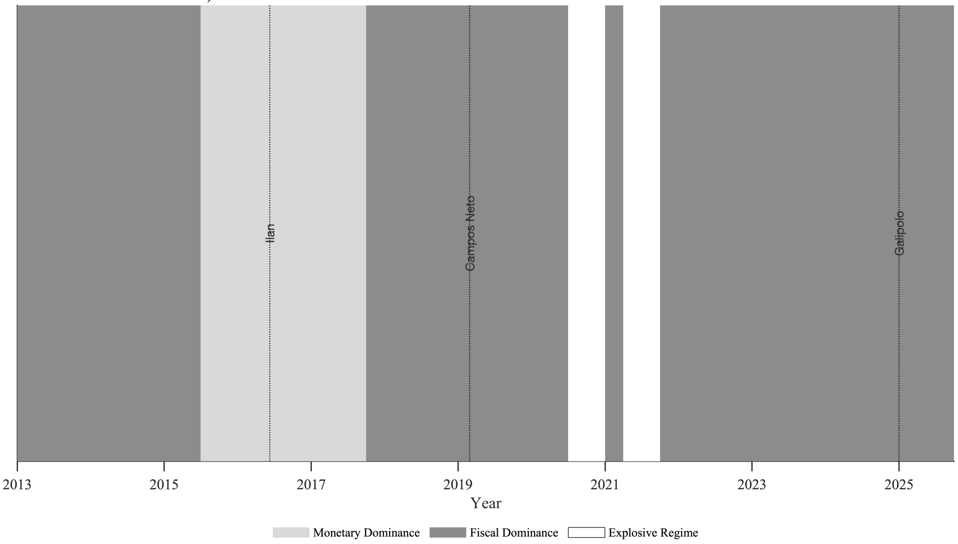
By contrast, the policy interest rate level, nominal public debt, and primary surplus exhibit relatively lower importance. While these variables remain relevant for regime identification, their informational content appears to be largely subsumed by the reaction coefficients and inflation dynamics, rather than by their levels alone. Overall, the feature importance analysis reinforces the view that regime classification is driven not merely by fiscal or monetary aggregates in isolation, but by the interaction between inflation dynamics, real activity, and the systematic responses of fiscal and monetary authorities.

6.4 Robustness

Given that inflation emerges as the most important variable for regime classification, we conduct a robustness exercise similar to that proposed by Hinterlang and Hollmayr (2022), in which the classification is re-estimated by replacing the baseline inflation index with an alternative proxy. In the present study, the baseline specification relies on the IPCA as the measure of consumer price inflation. To assess whether the results are sensitive to the choice of inflation index, the classification procedure is repeated using the IPC (CPI), calculated by the Getulio Vargas Foundation (FGV), as an alternative inflation measure.

The regime classification obtained using the IPC as the inflation index is identical to that reported in Figure 7, as shown in Figure 10. This result indicates that the inferred regime chronology is robust to changes in the inflation measure employed.

Figure 10: Historical Classification of Fiscal–Monetary Policy Regimes (IPC as inflation index)



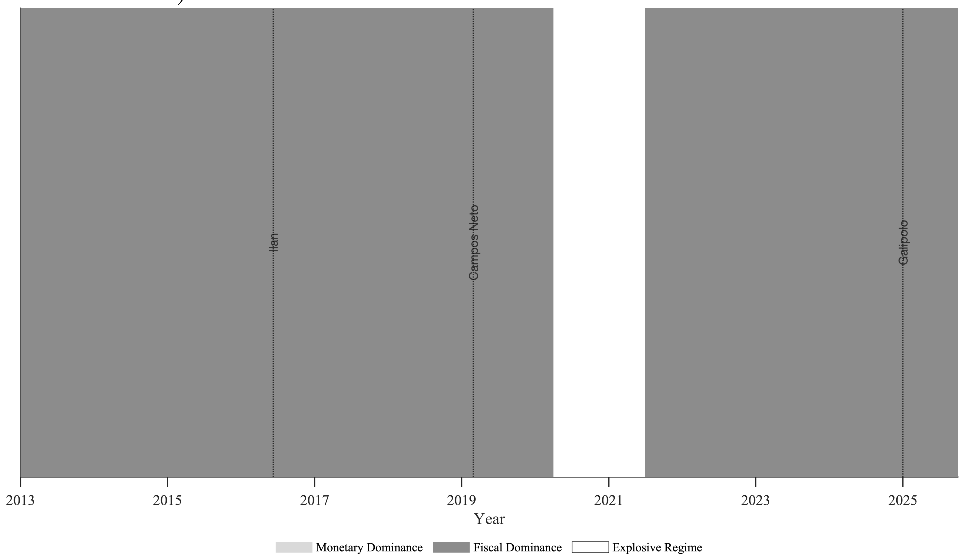
Notes: Dark gray areas indicate Fiscal Dominance, light gray areas indicate Monetary Dominance, and white areas correspond to the Explosive Regime. Dotted vertical lines mark Central Bank presidential appointment periods. Source: Author's elaboration.

Additionally, the robustness of the classification with respect to the method used to extract the cyclical component is also evaluated. To this end, the Hodrick–Prescott (HP) filter employed in the baseline specification is replaced by a Kalman filter based on an unobserved-components model, and the classification procedure is re-estimated. Figure 11 presents the historical classification of fiscal–monetary policy regimes obtained using the Kalman filter.

When the Hodrick–Prescott filter is replaced by a Kalman filter based on an unobserved-components model, the classification results remain unchanged for the fiscal dominance and explosive regimes. However, the period previously identified as monetary dominance is no longer detected. This result indicates that the identification of a monetary dominance regime is more sensitive to the method used to extract cyclical fluctuations, whereas the fiscal dominance and explosive regimes are robust to alternative filtering techniques.

From an economic perspective, this finding suggests that the Brazilian experience of monetary dominance is less clear-cut and may depend on how temporary versus permanent components of real economic activity are modeled. In contrast, periods characterized by fiscal stress or by the simultaneous and active stance of fiscal and monetary authorities, such as the pandemic episode, are robustly identified across specifications. Overall, these results re-

Figure 11: Historical Classification of Fiscal–Monetary Policy Regimes (Kalman Filter)



Notes: Dark gray areas indicate Fiscal Dominance, light gray areas indicate Monetary Dominance, and white areas correspond to the Explosive Regime. Dotted vertical lines mark Central Bank presidential appointment periods. Source: Author's elaboration.

inforce the view that fiscal-related regimes are more strongly supported by the data, while monetary dominance appears to be more episodic and sensitive to modeling assumptions.

Interestingly, the same interval is consistently classified as an explosive regime across all three empirical exercises. The explosive regime, as defined by Leeper (1991), corresponds to a region of price-level indeterminacy that may arise when both fiscal and monetary policies operate in an active manner. To assess whether inflation dynamics exhibited unusually high persistence during the pandemic period, we apply standard unit root tests to the monthly IPCA inflation series over the relevant sample.

At the 5% significance level, the Augmented Dickey–Fuller test fails to reject the null hypothesis of a unit root ($p = 0.072$), while the KPSS test rejects the null hypothesis of stationarity ($p = 0.0498$). Taken together, these results indicate that monthly inflation over this sample window should be treated as non-stationary[13]. Given the short sample size, the tests have limited power, but the joint evidence points to elevated persistence in inflation dynamics during this period. This pattern is consistent with the model's identification of an explosive regime, in which price dynamics become weakly anchored.

[13]The results reported here correspond to tests estimated with a constant. Results for the alternative deterministic specifications can be found in Table C.1 in the Appendix.

7 Conclusions

This dissertation investigated the interactions between fiscal and monetary policies in Brazil through a hybrid methodological framework first proposed by Hinterlang and Hollmayr (2022), which combines a regime-switching DSGE (MS-DSGE) model with supervised machine learning techniques. In this approach, the structural model operates as a data-generating process, allowing the training of classification algorithms that are subsequently applied to real Brazilian macroeconomic data.

It is important to emphasize that this approach is not intended to provide a structural estimator of policy regimes in the traditional econometric sense. Instead, it operates as a classifier that learns patterns from synthetic data generated by a theoretically grounded structural model. By identifying these behavioral signatures, the model helps connect structural macroeconomic theory with empirical regime classification.

Among the evaluated algorithms, XGBoost delivered the strongest training performance, achieving an accuracy of 95% and the best probabilistic calibration among the competing classifiers. The classification produced by this model indicates that Brazil is predominantly associated with fiscal dominance during much of the period linked to the New Economic Matrix. In contrast, the 2016 to 2017 interval following the implementation of the expenditure ceiling is classified as a phase of monetary dominance, consistent with the emergence of a new fiscal anchor and the Central Bank's success in re-anchoring inflation expectations. An additional contribution of the analysis is the identification of an explosive regime during the peak of the COVID-19 pandemic from 2020Q3 to 2021Q3, a period in which both fiscal and monetary authorities appear simultaneously active. This classification is further supported by standard unit root tests, namely ADF and KPSS, which point to heightened macroeconomic instability during that window.

For the post-pandemic period, the classification results are consistent with a return to fiscal dominance. This interpretation should nevertheless be understood as conditional on the methodological choices and modeling assumptions underlying the analysis.

From a methodological perspective, despite the well-known limitations of machine learning techniques in terms of interpretability and the inherently unobservable nature of fiscal–monetary interaction regimes, the results indicate that their integration with structural models is a promising strategy for regime identification. The proposed framework should therefore be viewed as a complement to traditional approaches, broadening the set of analytical tools available to macroeconomists and policymakers.

Several natural extensions follow from this work. These include introducing endogenous transition probabilities, considering alternative fiscal rules, and extending the model to an open-economy environment in order to explicitly incorporate exchange-rate transmission channels. Future research should also develop more robust strategies for estimating unobservable parameters. Although rolling-window OLS estimations improved classification performance metrics such as accuracy, AUC, and log-loss, an important limitation remains: nonlinear structural parameters are being approximated using linear specifications. Reducing this mismatch between the nonlinear theoretical structure and linear estimation methods is an important direction for further research.

This dissertation should not be interpreted as a definitive historical classification of Brazilian fiscal–monetary regimes, nor as a proposal to replace traditional macroeconometric methods with the approach developed here. Rather, it should be understood as a methodological contribution showing that structurally disciplined synthetic data, when combined with machine learning classification, can expand the empirical toolkit available for detecting non-observable macroeconomic phenomena, particularly in the Brazilian context.

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Appendix

A Structural Model

A.1 Model Calibration

Table A.1: Model calibration (quarterly data) — three-regime specification

Symbol	Description	Value (Regimes 1/2/3)
Preference Parameters		
β	Discount factor	0.985
σ	Inverse of the intertemporal elasticity of substitution	2.0
φ	Inverse of the Frisch elasticity of labor supply	1.0
Technology and Nominal Rigidities		
α	Capital share	1/3
θ	Calvo price stickiness	2/3
ε	Elasticity of substitution (markup)	5.0
Policy Parameters		
ϕ_y	Output feedback in the monetary policy rule	0.16
$\phi_\pi(r_t)$	Inflation feedback in the Taylor rule	1.5 / 0.5 / 1.5
$\Delta_B(r_t)$	Fiscal feedback on debt (primary surplus rule)	0.5 / 0.0 / 0.0
Δ_Y	Output feedback in the fiscal rule	0.2
ρ_{sp}	Persistence of the primary surplus	0.2
$\bar{s}$	Primary surplus target (% of steady-state output)	1%
g	Government spending share of output (steady state)	0.20
AR(1) Shock Processes		
ρ_A	Technology shock	0.90
ρ_Z	Preference shock	0.31
ρ_ν	Monetary policy shock	0.42
ρ_f	Fiscal shock	0.76
Shock Standard Deviations		
σ_A	Technology shock	0.01
σ_Z	Preference shock	0.01
σ_ν	Monetary policy shock	0.035
σ_f	Fiscal shock	0.01

Note: The model is calibrated using parameter values commonly adopted in the Brazilian macroeconomic literature.

B Machine Learning

B.1 Hyperparameter Selection

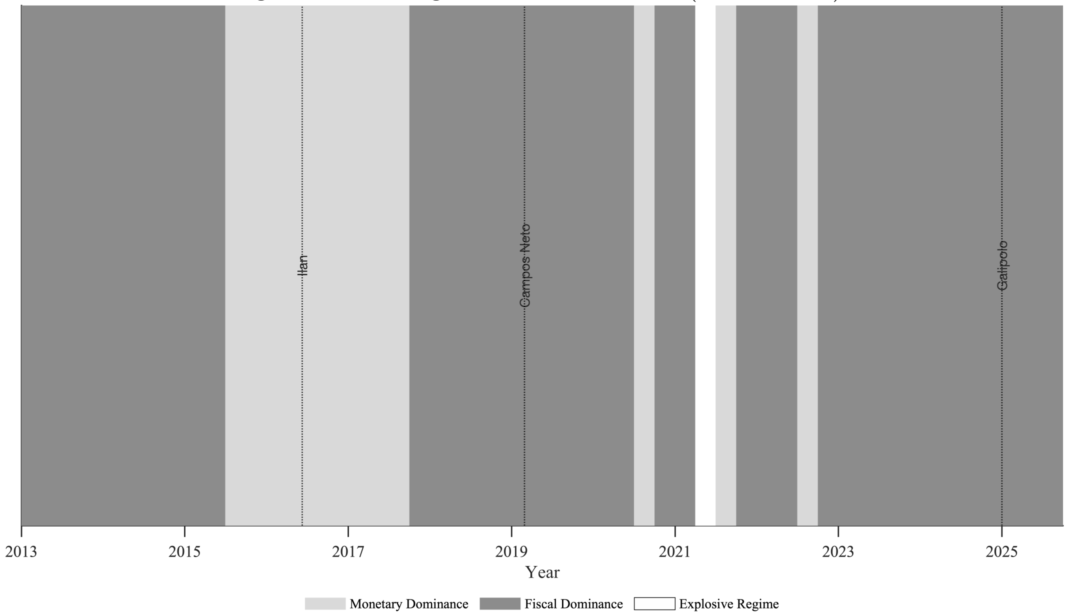
Table B.1: Optimized hyperparameters for machine learning classifiers

Model	**Hyperparameter**	**Value**
KNN	Number of neighbors (K)	56
Random Forest (RF)	Number of trees	1300
	Maximum tree depth	27
	Minimum samples per leaf	1
XGBoost	Learning rate (η)	0.07
	Maximum tree depth	6
	Minimum child weight	5.52
	Subsample ratio	0.68
	Column subsample (per tree)	0.63
	Regularization (λ)	0.78
AdaBoost	Number of estimators	775
	Learning rate	0.74
	Maximum tree depth	6
	Minimum samples per leaf	9
SVM (RBF)	Regularization parameter (C)	24.90
	Kernel scale (γ)	0.054
Decision Tree	Maximum tree depth	12
	Minimum samples per split	43
	Minimum samples per leaf	17
	Cost-complexity pruning (α)	0.0031

Note: Hyperparameters were selected using k-fold cross-validation combined with Bayesian optimization, with the objective of minimizing the multiclass log-loss on the validation set.

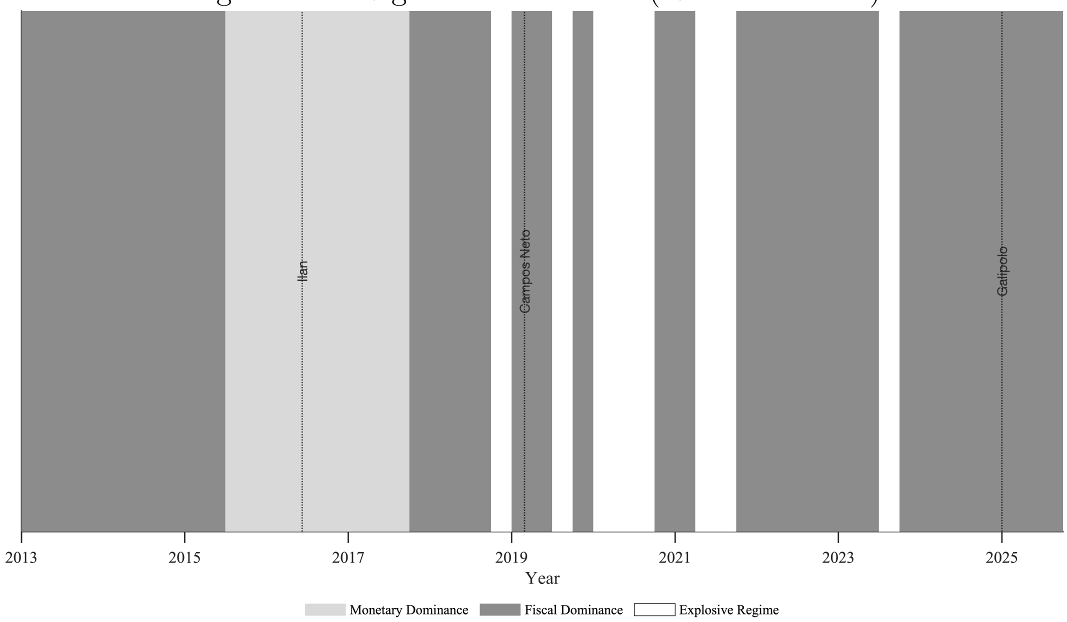
B.2 Classification Results of Alternative Models

Figure B.1: Regime classification (AdaBoost)



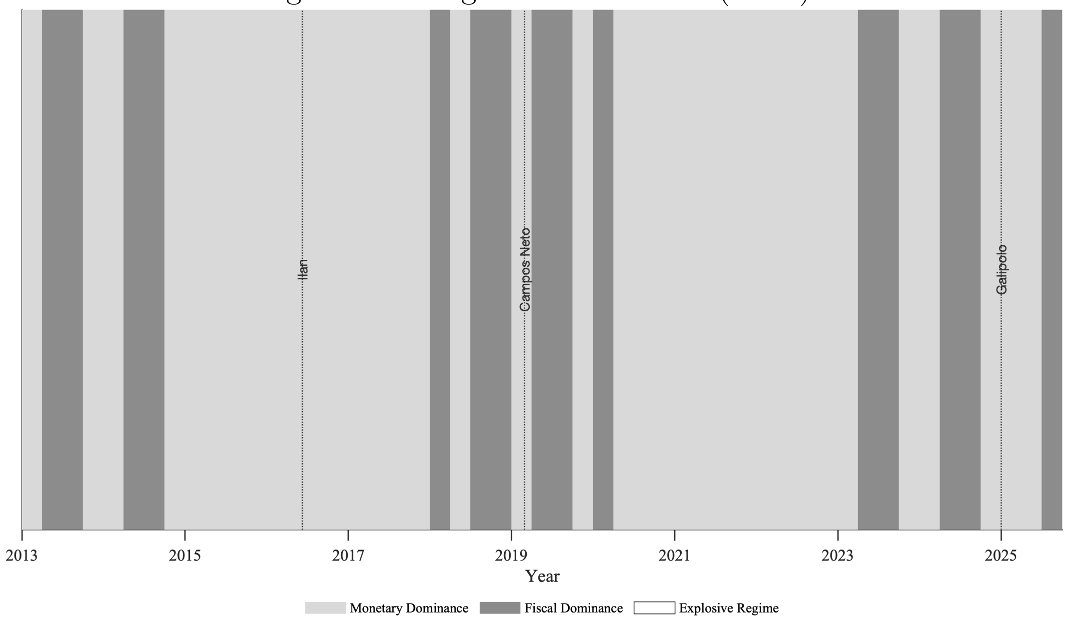
Source: Author's elaboration.

Figure B.2: Regime classification (Random Forest)



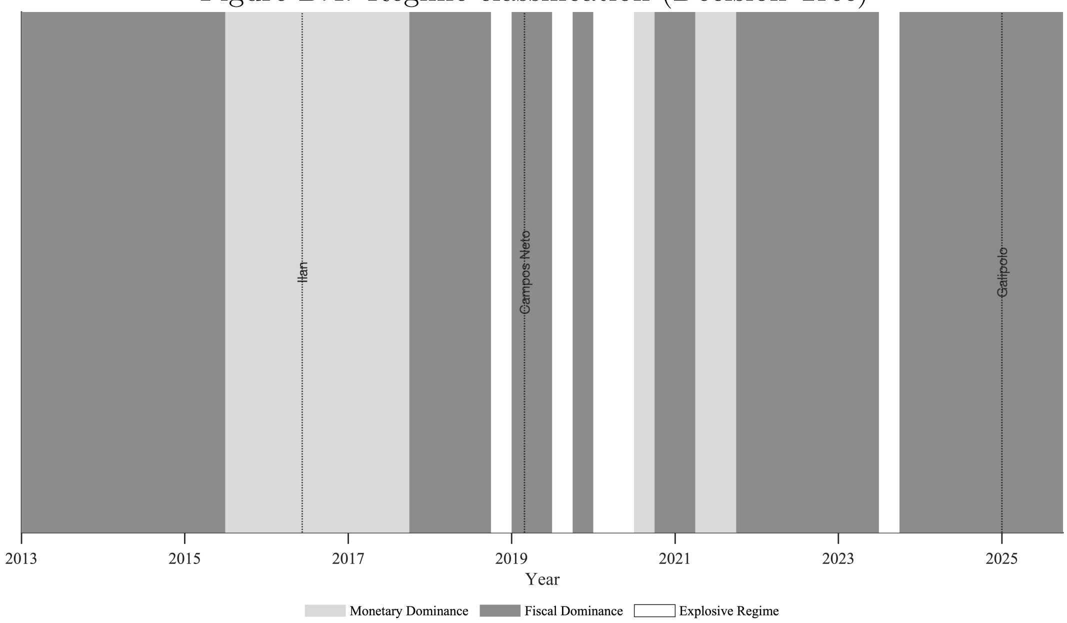
Source: Author's elaboration.

Figure B.3: Regime classification (SVM)



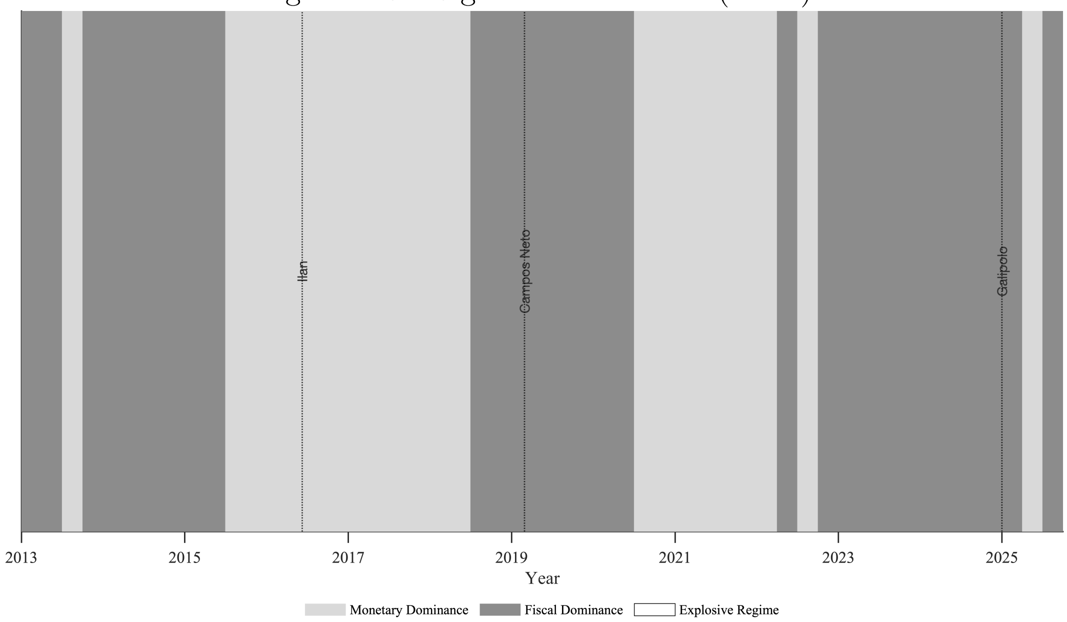
Source: Author's elaboration.

Figure B.4: Regime classification (Decision Tree)



Source: Author's elaboration.

Figure B.5: Regime classification (KNN)



Source: Author's elaboration.

B.3 Confusion Matrices

Table B.2: Confusion matrices for regime classification across models

Model	True Regime	MD (1)	FD (2)	EX (3)
XGBoost	MD (1)	2480	11	5
	FD (2)	80	330	6
	EX (3)	56	3	18
Decision Tree	MD (1)	2482	14	0
	FD (2)	123	292	1
	EX (3)	68	7	2
SVM	MD (1)	2492	4	0
	FD (2)	126	290	0
	EX (3)	76	1	0
Random Forest	MD (1)	2489	7	0
	FD (2)	92	320	4
	EX (3)	56	5	16
KNN	MD (1)	4114	29	17
	FD (2)	174	518	2
	EX (3)	92	5	30
AdaBoost	MD (1)	2488	7	1
	FD (2)	111	305	0
	EX (3)	60	2	15

Note: Rows correspond to true regimes and columns to predicted regimes. Regimes are defined as Monetary Dominance (MD), Fiscal Dominance (FD), and Explosive (EX).
Source: Author's elaboration.

B.4 XGBoost Regime Classification and Predicted Probabilities

Table B.3: Quarterly Regime Classification and Predicted Probabilities — XGBoost (Without Rolling-Window Estimated Features)

Quarter	**Regime**	**P(MD)**	**P(FD)**	**P(EX)**
2013.1	FD	0.02	0.97	0.01
2013.2	FD	0.02	0.98	0.00
2013.3	FD	0.36	0.64	0.00
2013.4	FD	0.01	0.98	0.00
2014.1	FD	0.01	0.98	0.01
2014.2	FD	0.01	0.98	0.01
2014.3	FD	0.01	0.98	0.01
2014.4	FD	0.01	0.99	0.01
2015.1	FD	0.01	0.99	0.01
2015.2	FD	0.03	0.94	0.03
2015.3	MD	0.59	0.13	0.28
2015.4	MD	0.83	0.04	0.12
2016.1	MD	0.92	0.03	0.05
2016.2	MD	0.92	0.03	0.05
2016.3	MD	0.86	0.02	0.12
2016.4	MD	0.96	0.01	0.03
2017.1	MD	0.86	0.02	0.12
2017.2	MD	0.91	0.02	0.07
2017.3	MD	0.61	0.10	0.28
2017.4	FD	0.01	0.90	0.10
2018.1	FD	0.00	0.94	0.06
2018.2	FD	0.00	0.96	0.03
2018.3	FD	0.00	0.96	0.04
2018.4	FD	0.01	0.90	0.10
2019.1	FD	0.00	0.96	0.04
2019.2	FD	0.00	0.97	0.03
2019.3	FD	0.02	0.91	0.08
2019.4	FD	0.00	0.98	0.02
2020.1	FD	0.00	0.96	0.04
2020.2	FD	0.05	0.70	0.24
2020.3	EX	0.12	0.05	0.83
2020.4	EX	0.02	0.45	0.53
2021.1	FD	0.01	0.50	0.49
2021.2	EX	0.02	0.37	0.61
2021.3	EX	0.05	0.22	0.73
2021.4	FD	0.00	0.94	0.06
2022.1	FD	0.01	0.88	0.11
2022.2	FD	0.00	0.96	0.04
2022.3	FD	0.01	0.95	0.04
2022.4	FD	0.00	0.98	0.02
2023.1	FD	0.00	0.98	0.02
2023.2	FD	0.00	0.97	0.03
2023.3	FD	0.00	0.96	0.04
2023.4	FD	0.00	0.95	0.05
2024.1	FD	0.00	0.96	0.04
2024.2	FD	0.00	0.94	0.06
2024.3	FD	0.00	0.96	0.04
2024.4	FD	0.00	0.97	0.03
2025.1	FD	0.00	0.91	0.09
2025.2	FD	0.00	0.95	0.05
2025.3	FD	0.00	0.86	0.14

Notes: MD = monetary dominance; FD = fiscal dominance; EX = explosive regime.
Source: Author's elaboration.

C Econometric Robustness

C.1 Unit Root Tests for Inflation

Table C.1: Unit root and stationarity tests for monthly inflation (IPCA, SGS 433), April 2020–June 2021

Test	**Spec**	**Test Statistic**	**p-value**
ADF (H_0: unit root)	c	-2.7093	0.0724
ADF (H_0: unit root)	ct	-2.7051	0.2340
ADF (H_0: unit root)	n	-1.1197	0.2386
KPSS (H_0: stationarity)	c	0.4640	0.0498
KPSS (H_0: stationarity)	ct	0.1853	0.0215

Notes: "c" denotes a constant, "ct" a constant and linear trend, and "n" no deterministic component. At the 5% significance level, the ADF test fails to reject the unit root null in all specifications, while the KPSS test rejects the null of stationarity in all specifications. Results therefore indicate non-stationarity of monthly inflation over this short sample window.

Source: Author's elaboration.

D Alternative Exercises

D.1 Dynare Exercise

In this section, a simulation exercise without transitional dynamics is conducted using Dynare. The analysis is based on two separate .mod files, each representing a distinct policy regime: Fiscal Dominance and Monetary Dominance. Rather than modeling regime changes explicitly, each regime is solved and simulated independently under a fixed policy configuration.

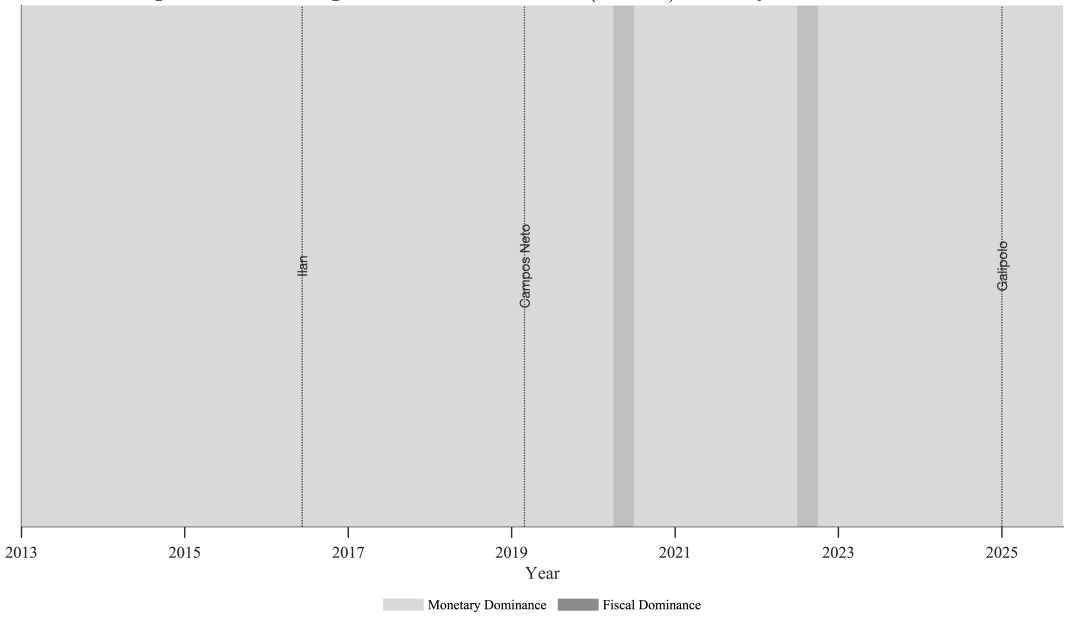
This approach is subject to two important methodological limitations. First, Dynare is not designed to solve models in which fiscal and monetary policies are simultaneously active in the sense required by regime-switching or mixed-policy equilibria. As a result, each regime must be analyzed in isolation. Second, the simulated data do not contain information about transitions between regimes, since the exercise abstracts from regime-switching dynamics and focuses exclusively on within-regime behavior.

Table D.1: Performance of Machine Learning Models (Dynare Exercise)

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Log Loss**	**AUC**
KNN	0.95	0.95	0.95	0.95	0.14	0.99
AdaBoost	0.97	0.97	0.97	0.97	0.27	1.00
Decision Tree	0.94	0.94	0.94	0.94	0.16	0.99
SVM	0.97	0.97	0.97	0.97	0.06	1.00
RF	0.97	0.97	0.97	0.97	0.08	1.00
XGBoost	0.97	0.97	0.97	0.97	0.07	1.00

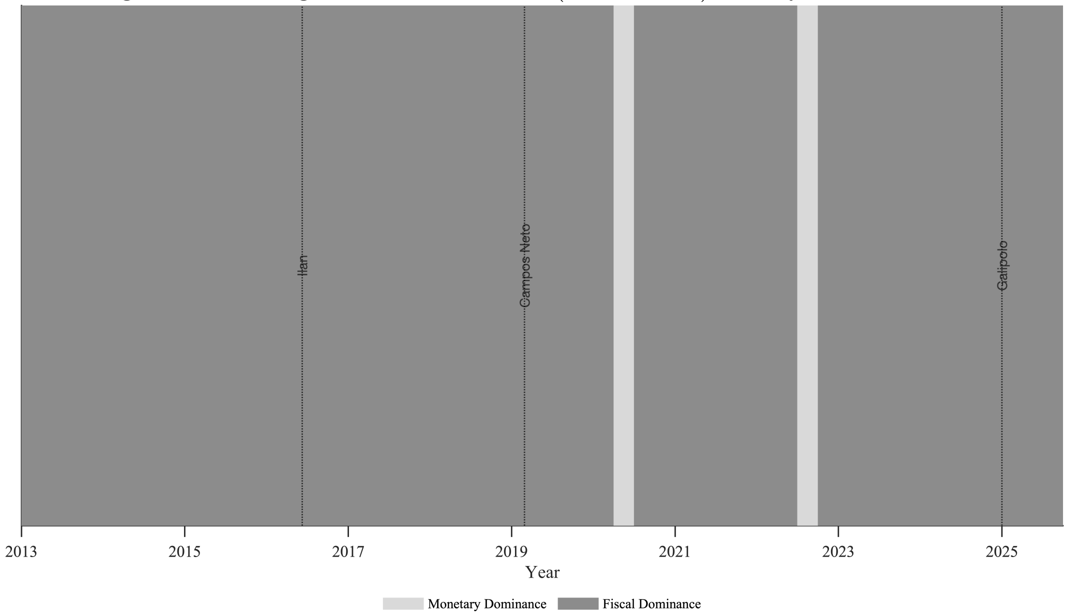
Source: Author's elaboration.

Figure D.1: Regime classification (KNN) — Dynare exercise



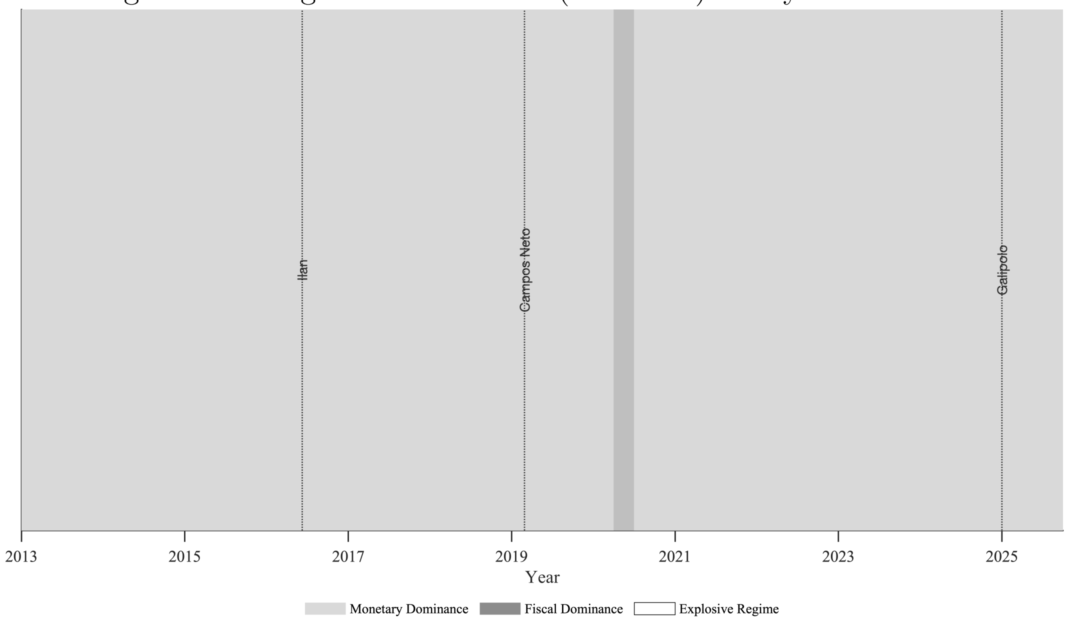
Source: Author's elaboration.

Figure D.2: Regime classification (AdaBoost) — Dynare exercise



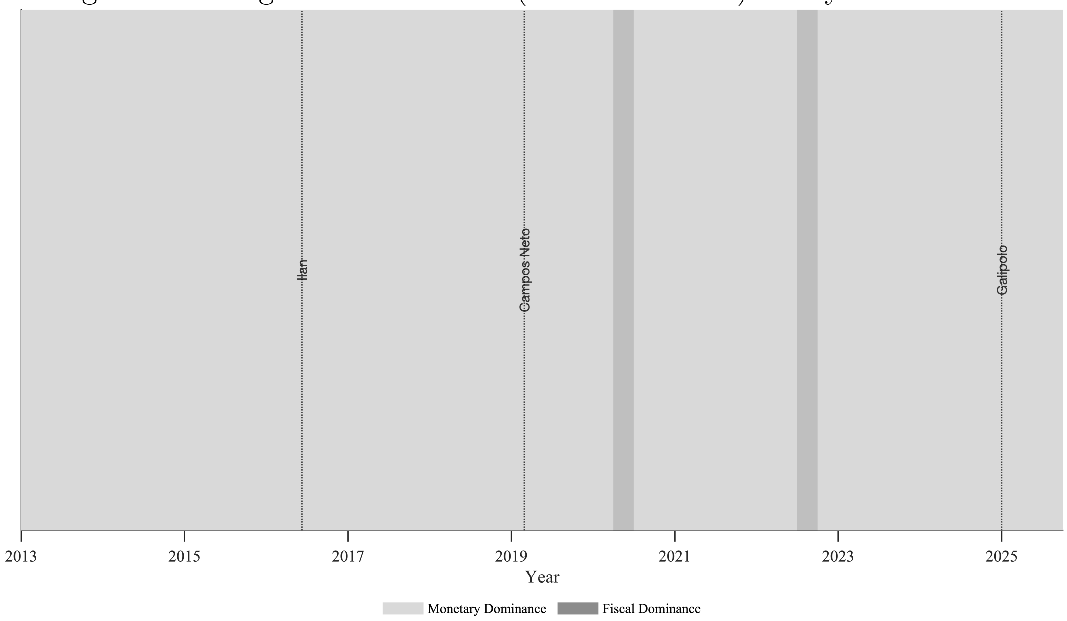
Source: Author's elaboration.

Figure D.3: Regime classification (XGBoost) — Dynare exercise



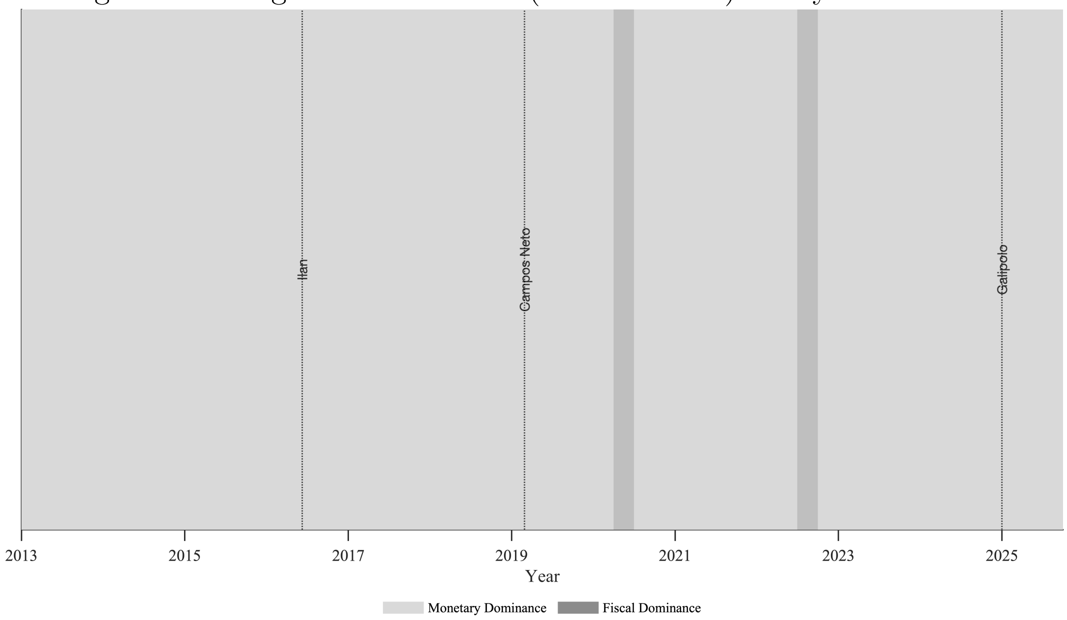
Source: Author's elaboration.

Figure D.4: Regime classification (Random Forest) — Dynare exercise



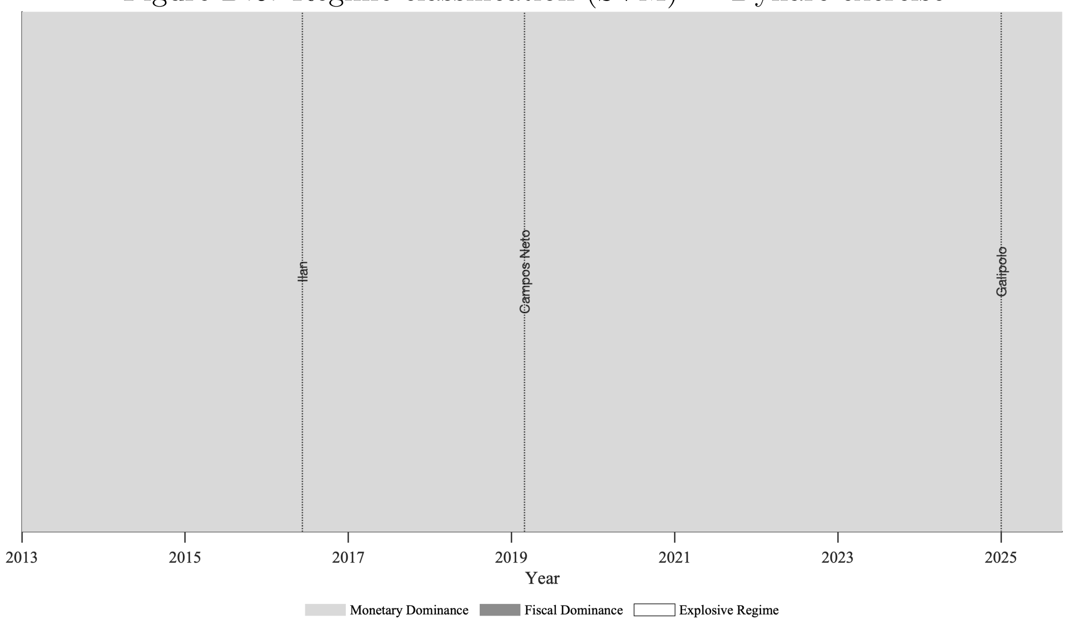
Source: Author's elaboration.

Figure D.5: Regime classification (Decision Tree) — Dynare exercise



Source: Author's elaboration.

Figure D.6: Regime classification (SVM) — Dynare exercise



Source: Author's elaboration.

D.2 Classification under Balanced Samples

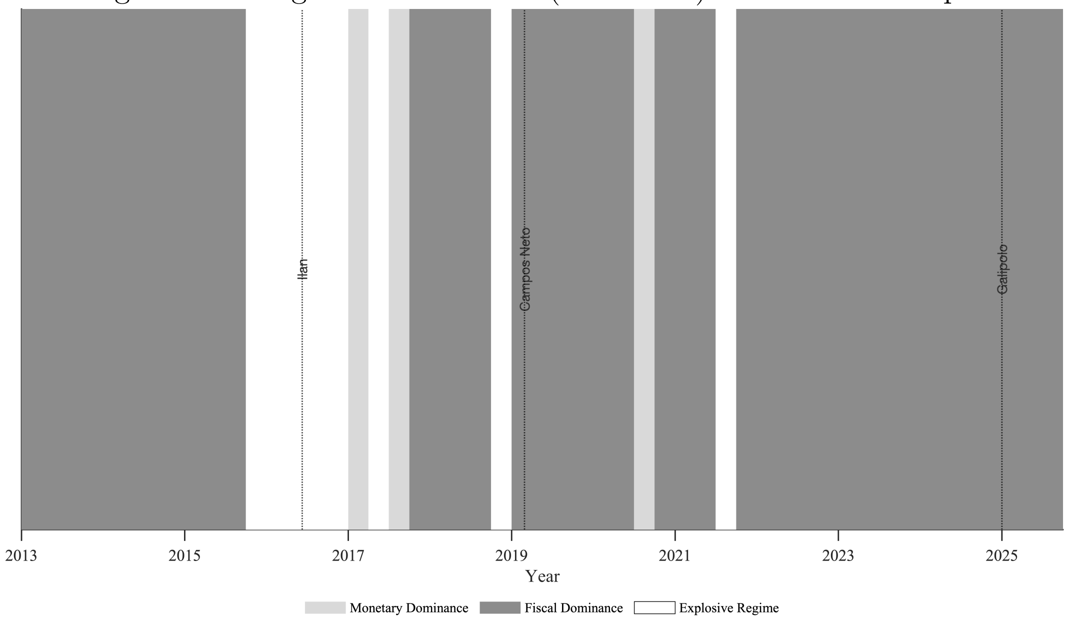
Balancing the sample substantially reduces classification performance across all models.

Table D.2: Performance of Machine Learning Models (Balanced Sample)

Model	Accuracy	Precision	Recall	F1-score	Log Loss	AUC
KNN	0.64	0.65	0.64	0.64	0.91	0.83
AdaBoost	0.64	0.64	0.64	0.64	1.08	0.82
Decision Tree	0.55	0.55	0.55	0.55	1.22	0.76
SVM	0.63	0.63	0.63	0.63	0.85	0.80
RF	0.67	0.67	0.67	0.67	0.73	0.85
XGBoost	0.68	0.67	0.67	0.67	0.72	0.85

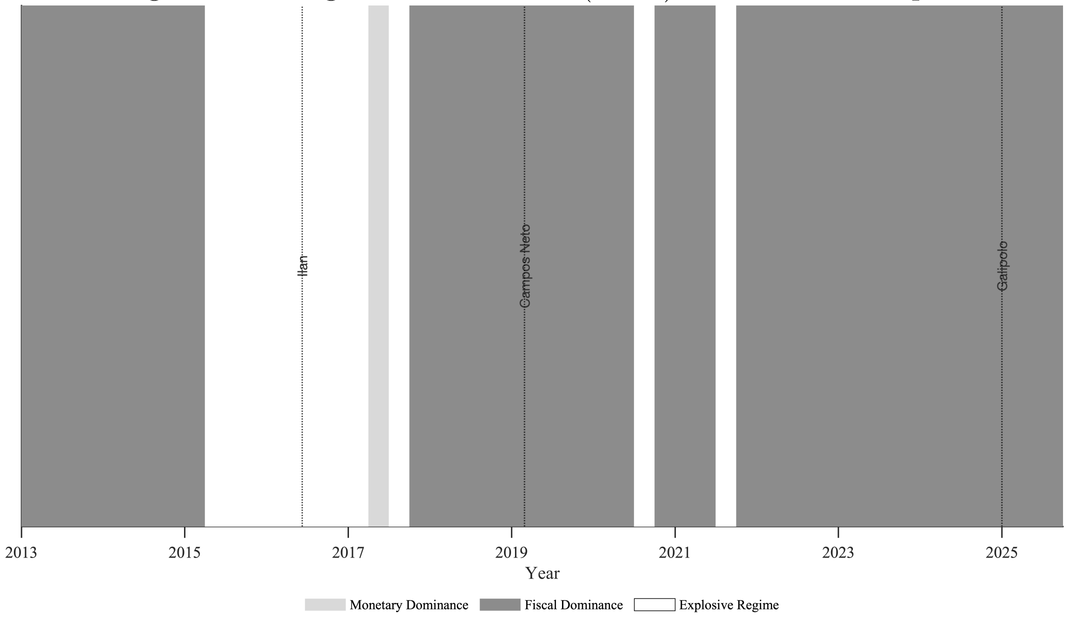
Source: Author's elaboration.

Figure D.7: Regime classification (AdaBoost) — balanced sample



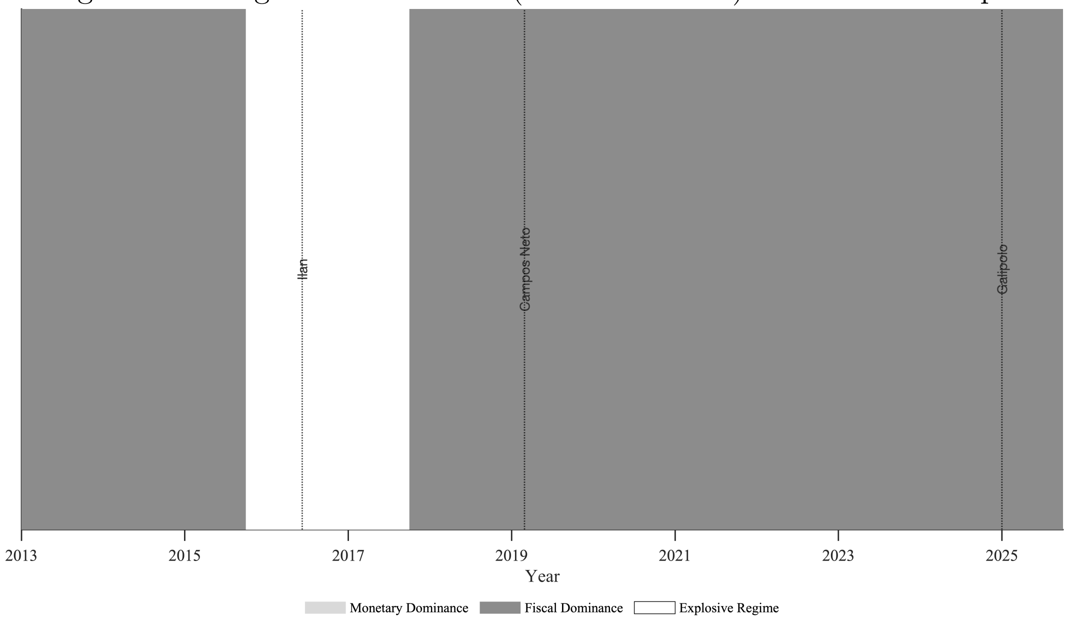
Source: Author's elaboration.

Figure D.8: Regime classification (KNN) — balanced sample



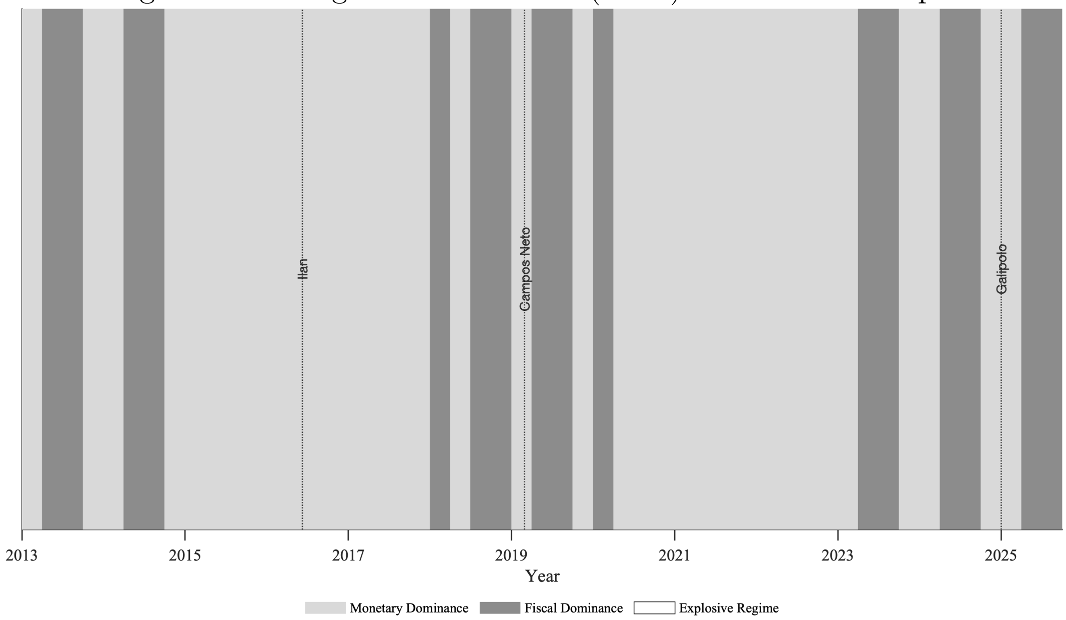
Source: Author's elaboration.

Figure D.9: Regime classification (Random Forest) — balanced sample



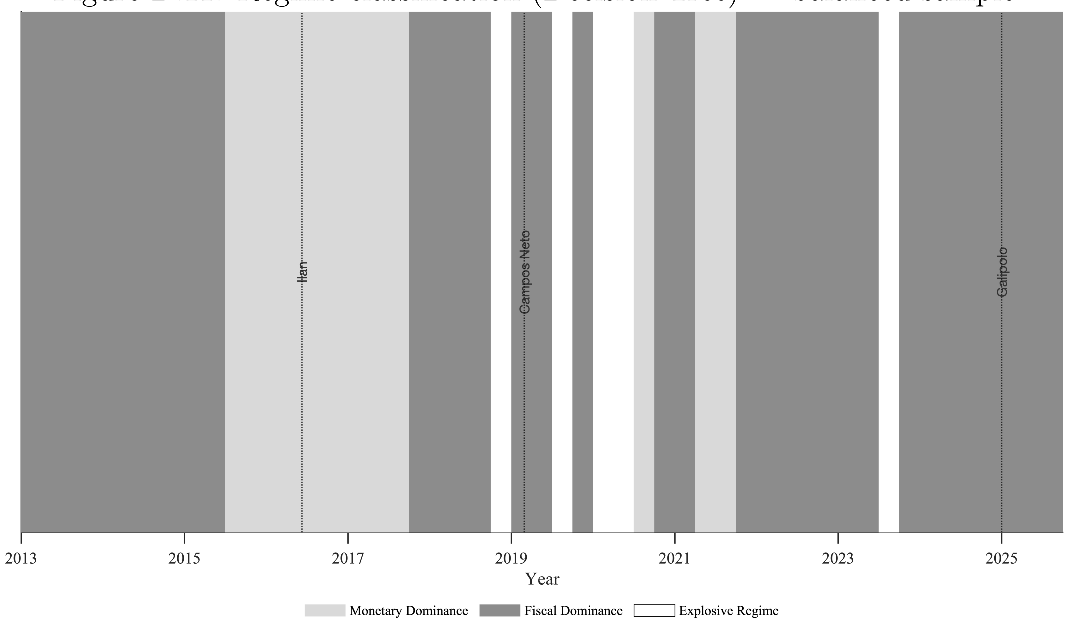
Source: Author's elaboration.

Figure D.10: Regime classification (SVM) — balanced sample



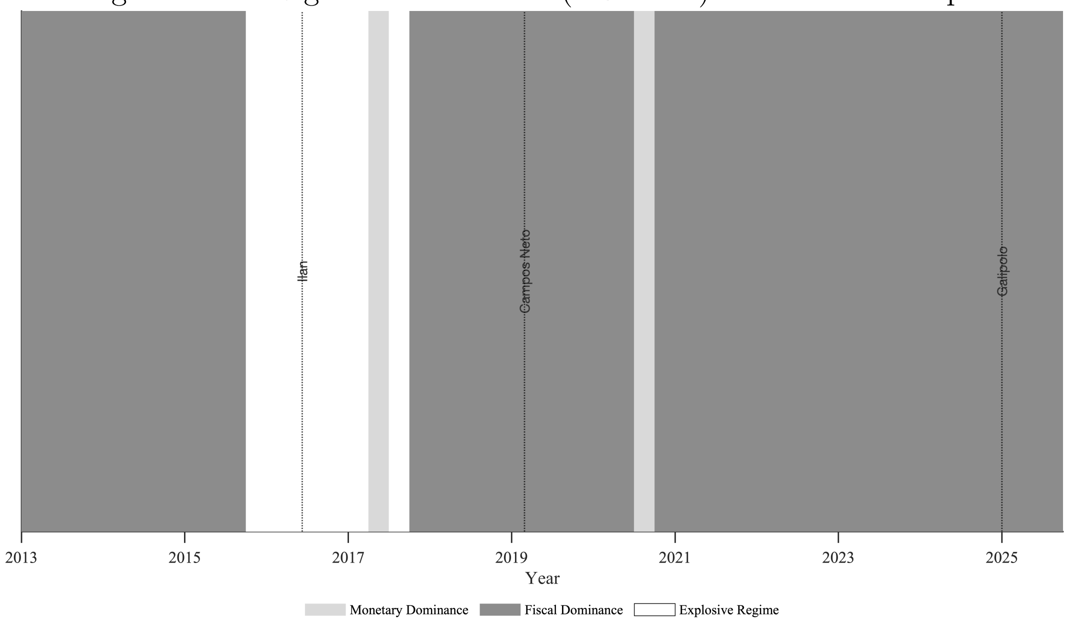
Source: Author's elaboration.

Figure D.11: Regime classification (Decision Tree) — balanced sample



Source: Author's elaboration.

Figure D.12: Regime classification (XGBoost) — balanced sample



Source: Author's elaboration.

D.3 Classification under Endogenous Probabilities

In this section, we present the results of an alternative exercise in which the transition probabilities across policy regimes are modeled as endogenous, rather than fixed over time. In contrast to the baseline specification, where regime transitions follow an exogenous Markov chain with constant probabilities, this extension allows the economy to switch regimes as a function of its own state variables.

Specifically, the probabilities of transitioning between regimes are governed by a multinomial logit structure, in which the likelihood of moving from one regime to another depends on deviations of the debt-to-output ratio from its steady state. Formally, the transition probabilities are defined as nonlinear functions of a state variable that captures fiscal stress, ensuring that probabilities remain bounded between zero and one and sum to unity within each row of the transition matrix.

This specification introduces an additional layer of economic discipline into the regime-switching process. Intuitively, higher levels of public indebtedness increase the probability of transitions toward regimes characterized by weaker fiscal adjustment or greater policy instability, while lower debt levels favor transitions toward regimes consistent with monetary dominance. As a result, regime changes are no longer purely stochastic events, but instead respond endogenously to the fiscal position of the economy.

From a modeling perspective, this extension substantially increases the complexity of the data-generating process. Endogenous transition probabilities introduce nonlinear feedback between macroeconomic outcomes, policy behavior, and regime dynamics, amplifying parameter interactions and increasing the dimensionality of the state space. While this specification is arguably more realistic from an economic standpoint, it also poses additional challenges for both the solution of the DSGE model and the subsequent machine learning classification task.

Table D.3 reports the performance of the machine learning classifiers trained on artificial data generated under endogenous regime-switching probabilities. Compared to the baseline case with exogenous transitions, classification performance deteriorates across all models, particularly in terms of probabilistic metrics such as Log Loss. This result reflects the fact that regime boundaries become less sharply defined when transitions depend continuously on state variables, making the separation between regimes inherently noisier.

Despite the overall decline in performance, ensemble methods continue to outperform simpler classifiers. XGBoost and Random Forest remain the best-performing models in terms of accuracy and AUC, while XGBoost again delivers the lowest Log Loss among all algorithms. This finding reinforces the robustness of tree-based ensemble methods in handling nonlinearities and complex interactions, even in settings where regime changes are endogenously determined.

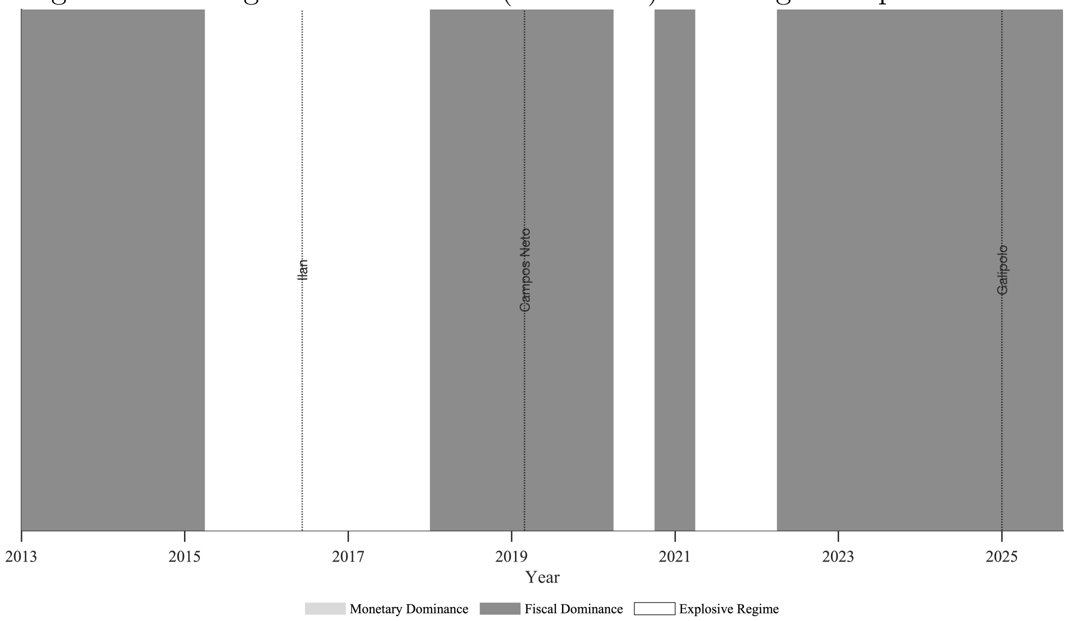
Overall, the endogenous-probability exercise should be interpreted as a robustness check rather than as a competing baseline specification. While it introduces a richer and more realistic mechanism for regime transitions, the loss in classification accuracy highlights the trade-off between economic realism and statistical separability. For this reason, the baseline analysis in the main text relies on exogenous transition probabilities, which offer a clearer mapping between theoretical regimes and empirical classification, while the present exercise illustrates the sensitivity of the results to alternative regime-switching assumptions.

Table D.3: Performance of Machine Learning Models (Endogenous Probabilities)

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Log Loss**	**AUC**
KNN	0.90	0.88	0.59	0.66	1.30	0.86
AdaBoost	0.92	0.92	0.68	0.75	0.99	0.92
Decision Tree	0.88	0.81	0.55	0.62	0.72	0.79
SVM	0.92	0.84	0.67	0.73	0.26	0.92
RF	0.91	0.92	0.66	0.74	0.26	0.93
XGBoost	0.92	0.91	0.69	0.77	0.23	0.94

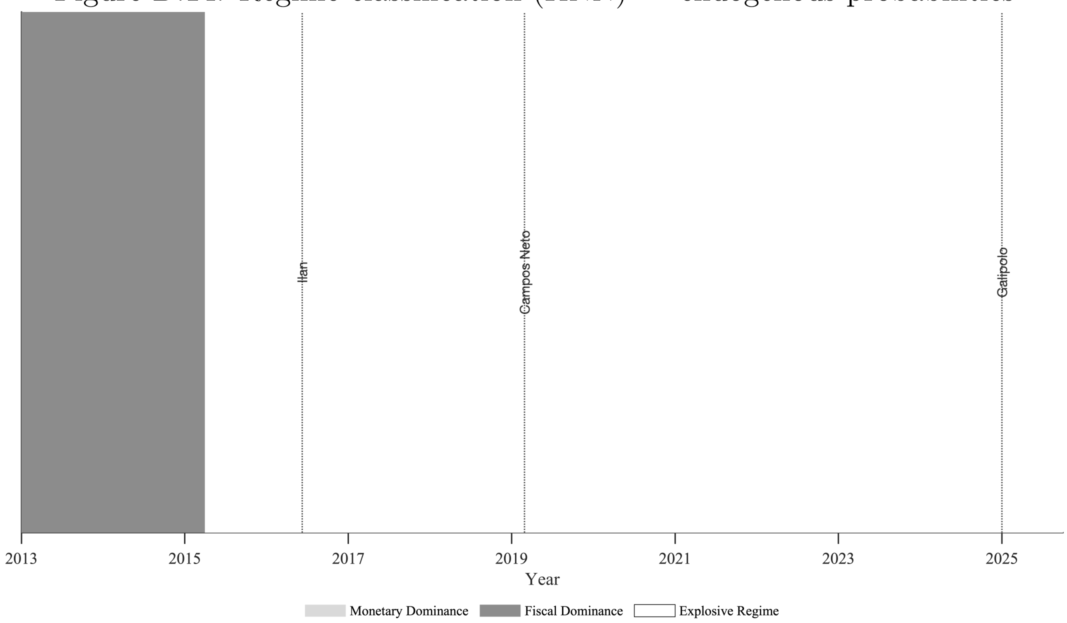
Source: Author's elaboration.

Figure D.13: Regime classification (AdaBoost) — endogenous probabilities



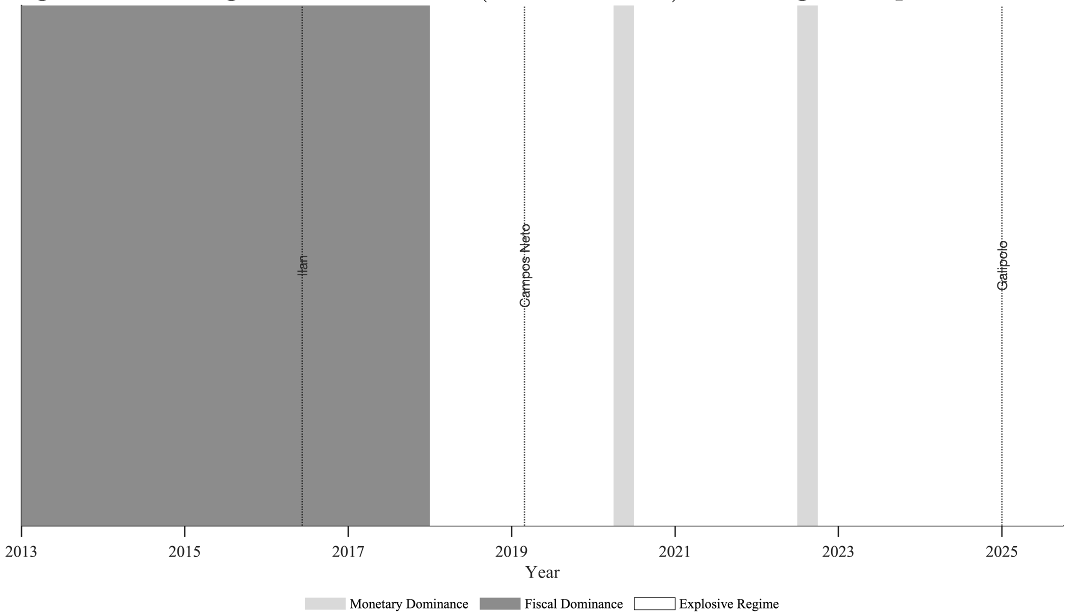
Source: Author's elaboration.

Figure D.14: Regime classification (KNN) — endogenous probabilities



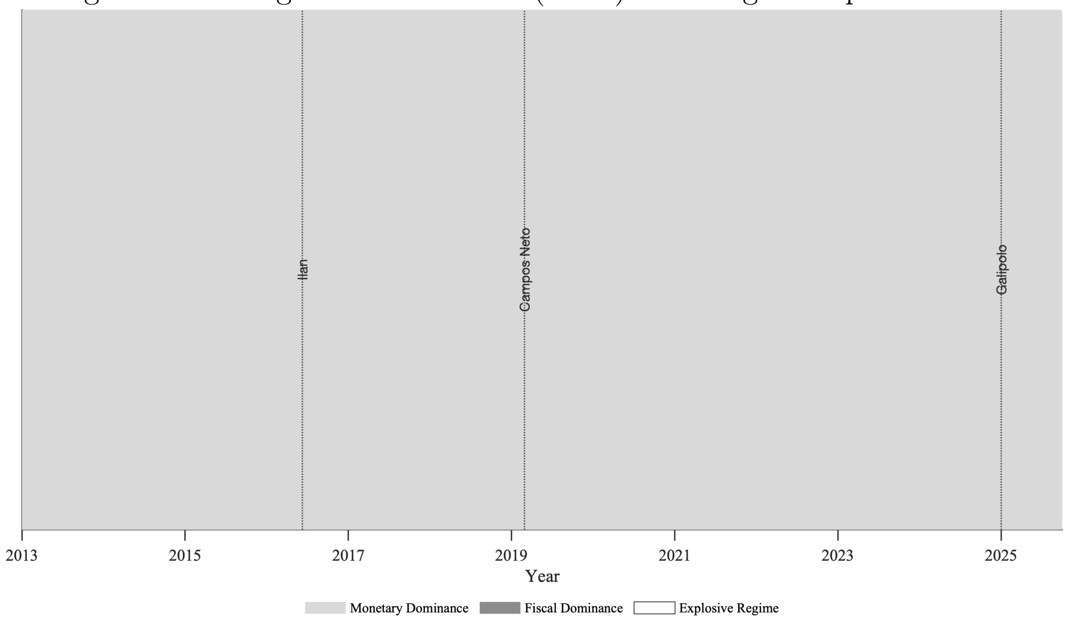
Source: Author's elaboration.

Figure D.15: Regime classification (Decision Tree) — endogenous probabilities



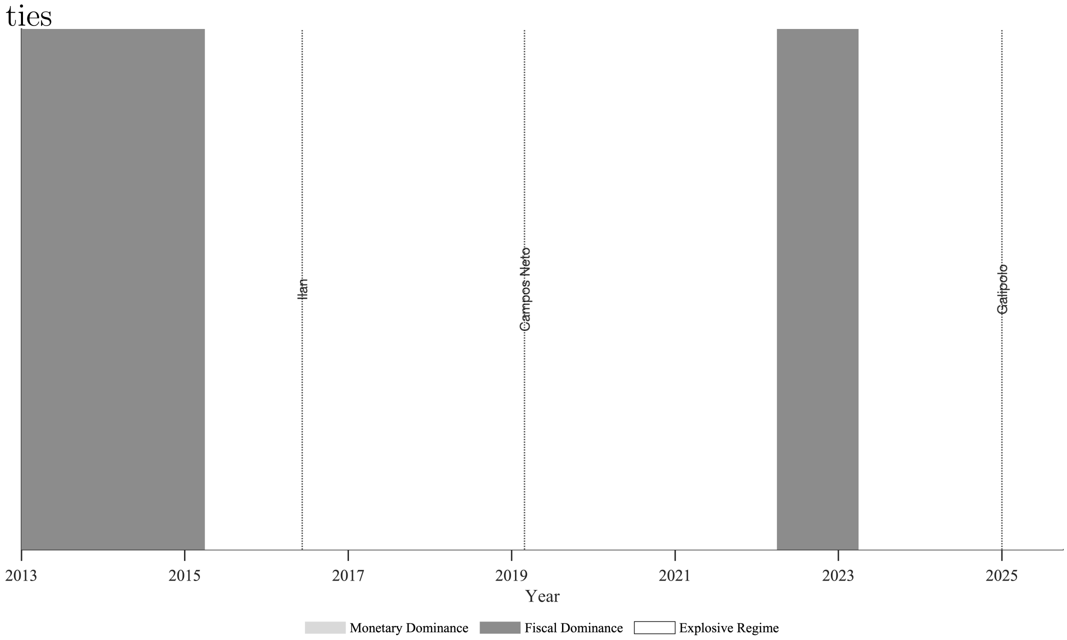
Source: Author's elaboration.

Figure D.16: Regime classification (SVM) — endogenous probabilities



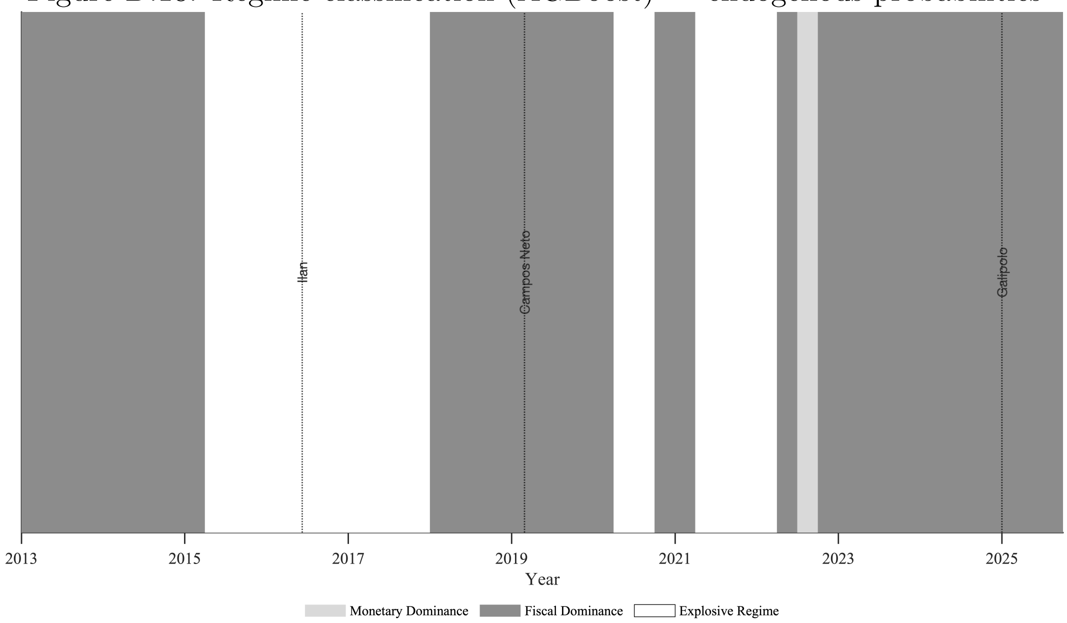
Source: Author's elaboration.

Figure D.17: Regime classification (Random Forest) — endogenous probabilities



Source: Author's elaboration.

Figure D.18: Regime classification (XGBoost) — endogenous probabilities



Source: Author's elaboration.

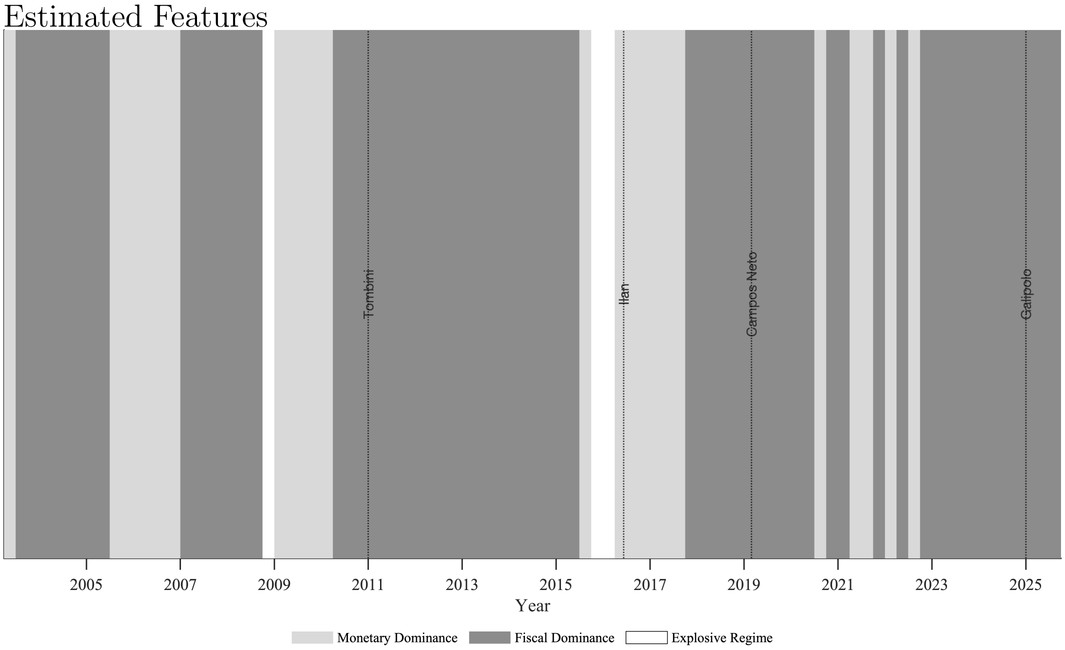
D.4 Classification without Rolling-Window Estimated Features

Table D.4: Performance of Machine Learning Models (Without Rolling-Window Estimated Features)

Model	Accuracy	Precision	Recall	F1-score	Log Loss	AUC
KNN	0.93	0.63	0.57	0.59	1.10	0.83
AdaBoost	0.93	0.77	0.63	0.67	0.99	0.87
Decision Tree	0.92	0.62	0.55	0.58	0.40	0.81
SVM	0.93	0.97	0.58	0.61	0.25	0.82
Random Forest	0.93	0.97	0.58	0.61	0.26	0.87
XGBoost	0.94	0.83	0.61	0.64	0.23	0.89

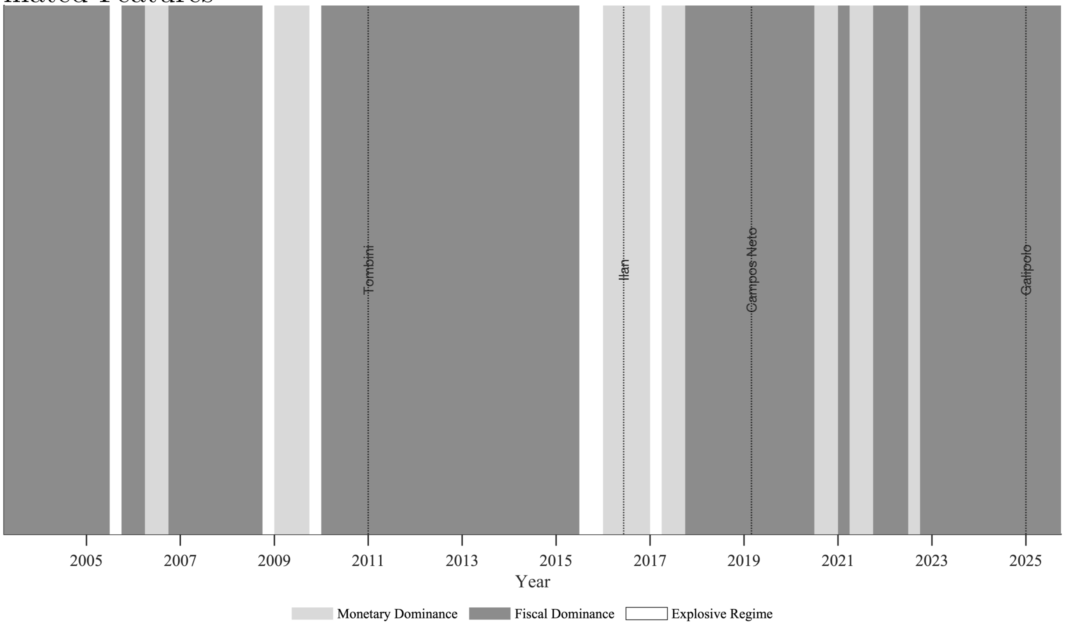
Source: Author's elaboration.

Figure D.19: Regime classification (AdaBoost) — without Rolling-Window Estimated Features



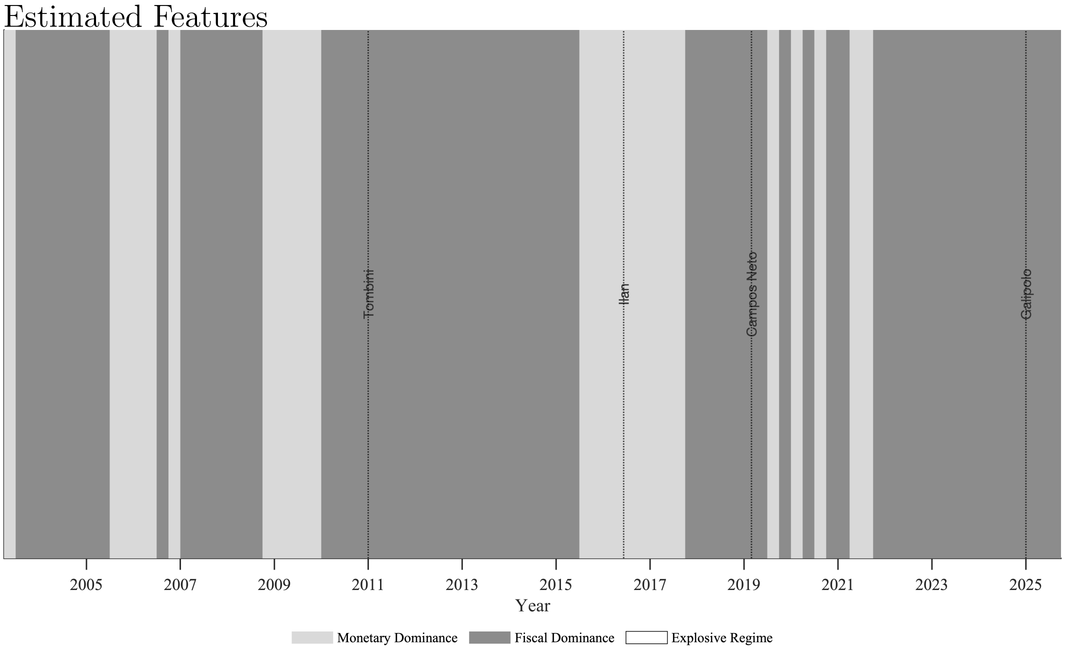
Source: Author's elaboration.

Figure D.20: Regime classification (KNN) — without Rolling-Window Estimated Features



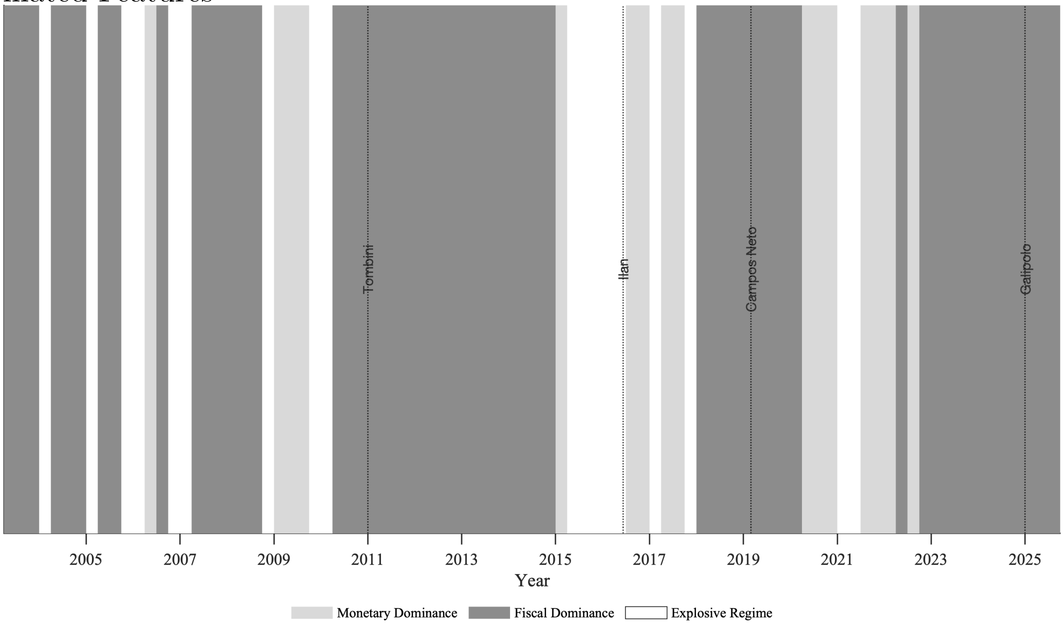
Source: Author's elaboration.

Figure D.21: Regime classification (Decision Tree) — without Rolling-Window Estimated Features



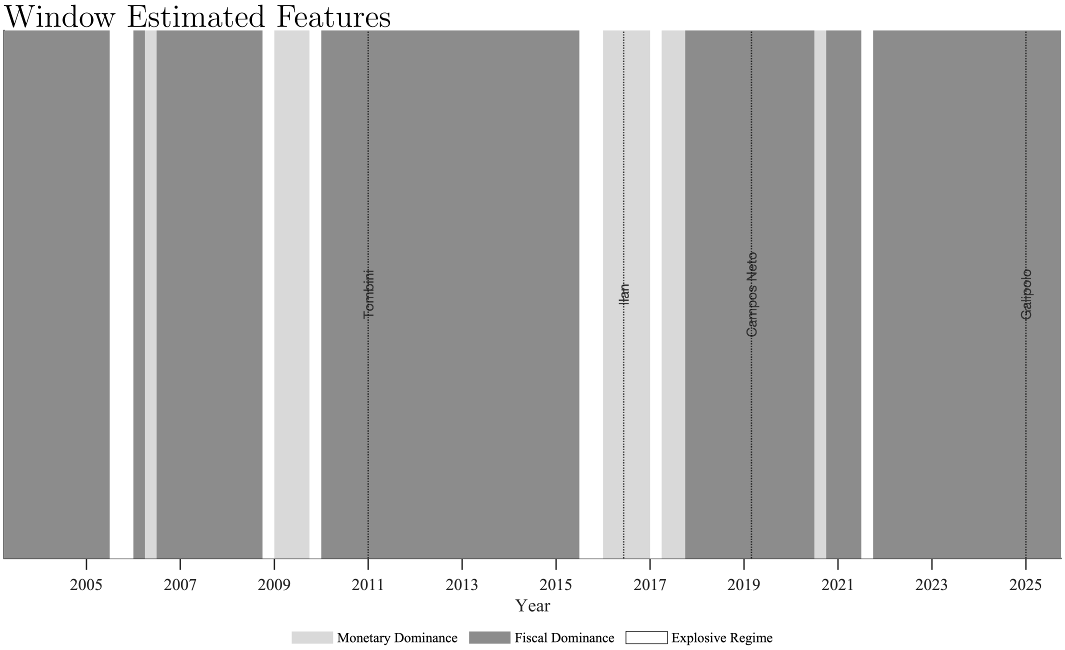
Source: Author's elaboration.

Figure D.22: Regime classification (SVM) — without Rolling-Window Estimated Features



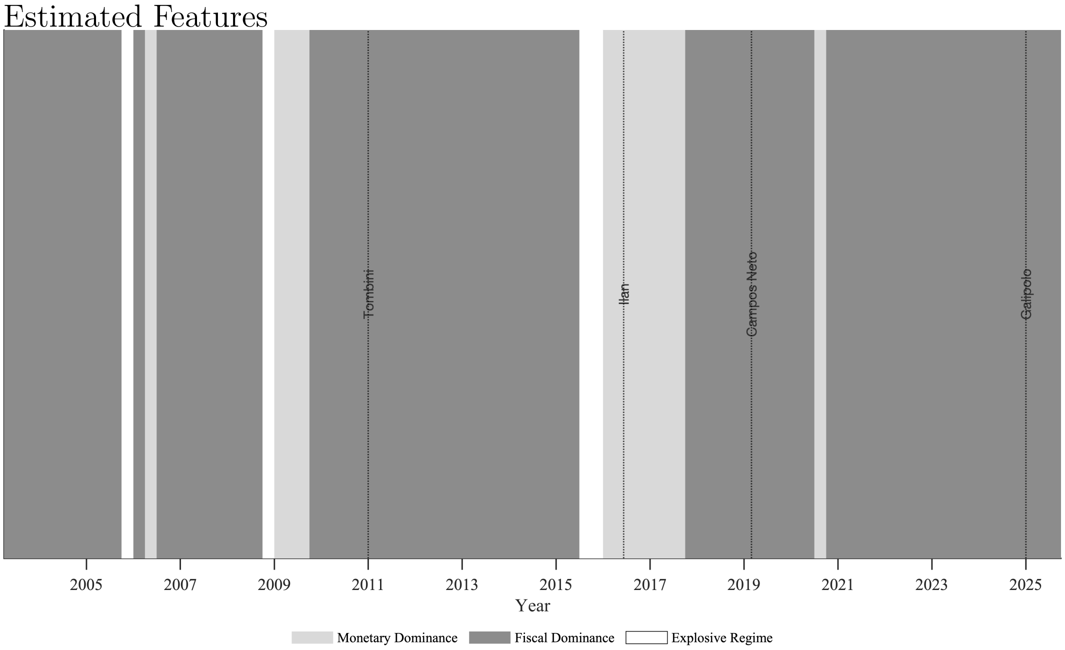
Source: Author's elaboration.

Figure D.23: Regime classification (Random Forest) — without Rolling-Window Estimated Features



Source: Author's elaboration.

Figure D.24: Regime classification (XGBoost) — without Rolling-Window Estimated Features



Source: Author's elaboration.