Hawkish or dovish? Risk premia and stocks' exposure to the Central Bank's stance*

Klaus Colletti Oehling†

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Abstract

The thesis investigates whether Brazilian equities' exposure to the Central Bank of Brazil's policy preferences constitutes a source of systematic risk. Following the Taylor rule specification of Clarida et al. (1998), a State-Space Model is used to estimate a time-varying coefficient for deviations of inflation from target. This series is then employed in Fama-MacBeth regressions to test the pricing implications of stocks' exposure to the Central Bank's stance. Results exhibit low statistical significance. While stocks positively exposed to a more hawkish policy stance – typically countercyclical firms – tend to present higher expected returns, this premium appears to reflect aggregate investor behavior rather than a common, non-diversifiable risk factor in the Brazilian equity market. As argued by Bali et al. (2017), countercyclical stocks are usually undervalued because they are often less preferred by investors.

Keywords: Monetary policy; risk premia; Central Bank preferences; asset pricing.

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†oehlingklaus@gmail.com

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"It is the small everyday deeds of ordinary folk that keep the darkness at bay. Small acts of kindness and love."

— J. R. R. Tolkien

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1 Introduction

It is evident from the recent literature, as shown in Sialm (2009), that fiscal shocks affect the trajectory of financial assets. At the same time, their political nature renders them subject to discretionary decisions, making them more uncertain and stochastic and, therefore, a potential source of systematic risk. In this context, Da et al. (2018) estimate a fiscal risk premium by analyzing how assets' exposure to fiscal policy explains their returns. In the realm of monetary policy, Bernanke and Kuttner (2005) have already shown, for the U.S. case, that such shocks also affect asset returns. However, the surprise component of shocks should not be present in monetary policy as it is in fiscal policy. This occurs for two main reasons: (1) there is a common objective – price and output stabilization; and (2) modern central banks are grounded in orthodox scientific principles and possess institutional autonomy. Therefore, the standardization of monetary policy conduct should keep expectations anchored, making its actions largely predictable and anticipated by the market, which reduces or even prevents the generation of risk premia.

Despite this, studies such as Owyang and Ramey (2004) indicate that, in the case of the Federal Reserve System (FED), there is regime switching. That is, the central bank's reaction function is not static: the weight assigned to inflation and economic activity varies over time. Carvalho and Muinhos (2022) also demonstrate this variability in Brazil. Such variation introduces additional uncertainty regarding the future conduct of monetary policy, implying that it can also constitute a source of systematic risk. Ozdagli and Velikov (2016) explore this issue and estimate a risk premium associated with exposure to monetary policy. However, the direct channel between the central bank's stance and asset returns has not yet been directly explored. Identifying firms' exposure to monetary policy as a priced risk would characterize the stance of the Central Bank of Brazil (Bacen) as a persistent source of risk premia, akin to factors such as value, size, or momentum in factor investing models.

The recent literature by Gürkaynak et al. (2005), Gilchrist and Zakrajšek (2012), Bernanke et al. (1996, 1999), and Campbell and Shiller (1988, 1998) provides evidence that there exists a theoretical link between the central bank's preferences and asset returns. In this context, the objective of the present study is to assess whether firms' exposure to the importance that the Bacen assigns to inflation in its interest rate decisions is priced. In other words, the study examines whether the regime changes identified in the literature can be interpreted as a systematic risk factor in the Brazilian financial market. First, a State-Space Model (SSM) is employed, using the Kalman (1960) filter, to estimate the unobservable variable corresponding to Bacen's stance within a New Keynesian Taylor rule. The time-varying parameter associated with the weight assigned by the central bank to inflation is then incorporated into an asset pricing model. At this stage, the Fama-MacBeth regression of Fama and MacBeth (1973) is used, which is the standard method in the literature for estimating risk premia. A set of factors identified as relevant by Fama and French (2015) is included as control variables. In addition to estimating the risk premium associated with exposure to Bacen's preferences, the study also draws conclusions regarding testable hypotheses based on the coefficients of the control variables. In this respect, the presence of risk premia for other classical factors, the validity of the Efficient Market Hypothesis (EMH), and the completeness of the models in terms of the use of a sufficient set of risk factors are assessed. Thus, although the primary objective is to estimate the risk premium associated with exposure to Bacen's stance, the study also contributes to the understanding of fundamental aspects of asset pricing in Brazil by providing empirical evidence on multiple risk factors. Accordingly, the central motivation is to contribute to the literature, either by incorporating or ruling out a new theoretically grounded – but previously unexplored – systematic risk factor, or by deepening the understanding of other factors in a market with a limited tradition in factor investing strategies.

To accomplish this, the present study is structured into five main parts. Following this brief introduction, a systematic review of the related topics is conducted: (1) the inflation-targeting regime and the central bank's reaction function; and (2) asset pricing and systematic risk factors. Next, the methodology is presented, specifying the theoretical and econometric models to be employed, as well as the data used and their transformations. Subsequently, the results and interpretations of all estimations are reported, including a section with descriptive analysis, another devoted to validating the models' hypotheses, and one presenting a robustness test exercise. Finally, the conclusion is provided, bringing the research question to a close.

2 A systematic review

Given the distinct nature of the multiple theories employed in this study, the review of the most relevant topics is organized into three sections. First, a concise overview of the body of knowledge surrounding the inflation-targeting regime is presented. This discussion culminates in central banks' reaction functions, with this stage adopting a more academic focus. Next, the same approach is applied to asset pricing, culminating in multifactor asset pricing models. Finally, a bridge between the two themes is established, highlighting the theoretical foundations and the research objective.

2.1 Inflation targeting regime

2.1.1 From exchange rate anchors to inflation targets

The history of monetary regimes worldwide is deeply marked by attempts to balance stability and economic flexibility. Since the nineteenth century, various institutional arrangements have been adopted in different countries with shared objectives. Priority centered on containing inflation, preserving the value of the currency, and ensuring confidence in markets.

One such experience was the classical gold standard, gradually adopted by the world's major economies between 1870 and 1914. Under this regime, monetary issuance was constrained by the quantity of available gold, which rendered inflation historically low, though not absent. As shown by Bordo and Kydland (1995), the discipline imposed by gold partially limited the discretion of monetary policy, albeit at the cost of a lack of flexibility during periods of crisis.

With the advent of World War I, gold convertibility was suspended by several nations. As noted by Eichengreen (1996), abandoning the standard allowed monetary issuance to be used as an emergency means of financing the massive deficits of countries at war. The interwar period was marked by global instability, and the return to the gold standard was limited and incomplete, in part due to the impact of the Great Depression. World War II then led to a new collapse of the system – this time definitive – which prompted its reformulation in 1944 under the Bretton Woods agreements, establishing the gold-dollar standard.

This new arrangement maintained the U.S. dollar as the central currency, pegged to gold, while other currencies fixed their values relative to the dollar. The system aimed to provide greater flexibility to monetary policy without requiring all countries to hold gold reserves. Moreover, it was highly convenient, as the United States held roughly two-thirds of the world's gold after World War II. This system remained in place until the 1960s, when rising U.S. government spending – driven by expansionary fiscal policies associated with the Vietnam War and the Great Society social agenda – led to monetary expansion without a proportional gold backing. This gradually eroded U.S. credibility and rendered the continuation of the system untenable.

The definitive collapse of the Bretton Woods system occurred in 1971, when U.S. President Richard Nixon decided to suspend the convertibility of the dollar into gold. This episode, known as the Nixon Shock, marked the transition to a pure fiat money regime. In the following years, countries around the world that were part of the system also gradually suspended the convertibility of their currencies into the dollar. Under this new regime, central banks no longer had a physical backing for their monetary issuance. For the first time, money was based entirely on trust.

The subsequent period was characterized by high inflation and global macroeconomic instability, especially during the oil crises of 1973 and 1979. Exchange rates were highly volatile, and there was instability in trade and capital flows worldwide. The world faced the challenge of anchoring inflation expectations without a fixed regime imposing exogenous discipline. It was during this period that Federal Reserve Chairman Paul Volcker led a phase of sharp monetary tightening in the United States. This episode became known as a successful example of monetary policy as a price stabilizer, marking the end of the era of high inflation and discretionary policy in the United States.

With the foundations of rule-based central bank behavior established, New Zealand adopted the inflation-targeting regime for the first time in history in December 1989. Gradually, throughout the 1990s, it was adopted by the world's major economies, including Brazil in 1999. The proposal, as discussed by Mishkin and Schmidt-Hebbel (2007), is to anchor expectations through transparency, predictability, and institutional accountability, achieved via explicit inflation targets. This arrangement is often justified as a response to the absence of an anchor such as gold or a fixed exchange rate. Therefore, the adoption of this regime can be understood not only as an institutional innovation, but as a necessity arising from the progressive abandonment of exogenous monetary control mechanisms in favor of greater economic flexibility.

The contractionary episode led by Paul Volcker in the early 1980s thus represented a decisive turning point in the conduct of monetary policy, laying the conceptual foundations for the development of the inflation-targeting regime. However, its impact is not limited to this aspect. By demonstrating a consistent pattern of action, this episode also motivated academics to understand the specific function governing the Federal Reserve's response.

2.1.2 The monetary policy rule

The literature on monetary rules was inaugurated by Taylor (1993). He defined the interest rate set by the Federal Reserve as a function of the output gap and the deviation of inflation from its target, defined as 2% per year. The well-known Taylor Rule follows Equation (1).

$$i = (\pi + \bar{r}) + \gamma\tilde{y} + \beta(\pi - 2) \tag{1}$$

Here, i denotes the nominal federal funds interest rate, π is the inflation rate over the previous four quarters, $\tilde{y}$ is the percentage deviation of real Gross Domestic Product (GDP) from potential GDP, $\bar{r}$ is the neutral real interest rate – assumed to be 2% per year – and γ and β are, respectively, the weights assigned to the output gap and to the deviation from the inflation target – both assumed to be equal to 0.5. Taylor (1993, p. 8) concludes that:

> What is perhaps surprising is that this rule fits the actual policy performance during the last few years remarkably well. [...] In this sense the Fed policy has been conducted as if the Fed had been following a policy rule much like the one called for by recent research on policy rules.

Therefore, the Taylor Rule explained the Federal Reserve's successful behavior during the 1980s remarkably well. In doing so, it established a quantitative framework for the conduct and evaluation of monetary policy. Its impact was profound, influencing not only central bank practice but also the formulation of modern macroeconomic models.

The next evolution of the central bank's reaction function stemmed from the implementation of an alternative monetary policy transmission mechanism within the Taylor Rule. The original formulation relied on the deviation of realized inflation from the target, implicitly assuming that inflation expectations could be approximated by past inflation. This interpretation is associated with the adaptive expectations framework implemented by Friedman (1968) in the Phillips curve proposed by Phelps (1967). In this formulation – Equation (2) – inflation depends on the deviation of output from its potential (y^e), weighted by a parameter ϕ, and on inflation expectations, defined as past inflation. However, this formulation had already been inconsistent with theory for decades.

$$\pi_t = \pi_{t-1} + \phi\big(y_t - y^e\big) \tag{2}$$

After the period of high inflation and stagnant output experienced in the United States during the 1970s and 1980s, the Phillips curve had lost its empirical validity. Lucas (1972) developed the entire rational expectations framework to fill this gap in the theory of monetary policy transmission. With the incorporation of this theory, agents use all available information – not only the past realization of the variable of interest – to form their expectations about that variable. This implies that, in the Taylor Rule, the deviation of inflation expectations from the target should be used, rather than the deviation of realized inflation from the target. The technical motivation is that, if expected inflation is the key determinant of current and future inflation, policy is more precise when it responds to expectations.

Another relevant modification proposed to the central bank's reaction function stemmed from the changes undergone by the Investment-Savings (IS) curve over the decades. The classical IS curve of Hicks (1937), derived from Keynes (1936), describes equilibrium in the goods market – where supply equals demand. It is a static relationship among output, consumption, investment, and government spending. Hall (1978) introduced an innovation by showing that aggregate consumption depends on expectations of future consumption and on the expected real interest rate. This formulation, known as the consumption Euler equation, became the seed of the intertemporal IS curve, initially derived by Rotemberg and Woodford (1997). They start from the premise that private investment responds to the same intertemporal incentives as consumption and assume that government spending is exogenous and therefore does not enter explicitly into the equation. That is, the core of aggregate demand – household consumption plus investment – is treated as a single intertemporal private spending decision, sensitive to the real interest rate and to expectations about future income. This is consistent with Friedman (1957)'s theory of intertemporal consumption smoothing, in which an agent decides whether to borrow or save based on such expectations.

This microeconomic foundation transformed the IS curve into a *forward-looking* relationship, as shown in Equation (3). In this equation, σ represents the intertemporal elasticity of substitution. The connection between this formulation and the Taylor Rule arises from the fact that the new basis of output is formed by expectations about it. That is, *ceteris paribus*, in the absence of changes in interest rates and inflation expectations, what determines output is the expectation of output itself. Therefore, monetary policy is more effective when it responds to expectations rather than to output itself.

$$y_t = \mathbb{E}_t\big[y_{t+1}\big] - \frac{1}{\sigma}\big(i_t - \mathbb{E}_t\big[\pi_{t+1}\big] - \bar{r}_t\big) \tag{3}$$

Clarida et al. (1998) unify this entire framework to formulate a Taylor Rule with the new monetary policy transmission channels. They use inflation expectations *à la* Lucas (1972) – $\mathbb{E}t\big[\pi t + 1\big]$ – and output expectations *à la* Rotemberg and Woodford (1997) – $\mathbb{E}t\big[yt + 1\big]$ – to establish a *forward-looking* Taylor Rule as defined by Equation (4). This reaction function is consistent with the New Keynesian school developed over the preceding decades. In it, π^T represents the inflation target.

$$i_t = \bar{r} + \pi^T + \beta\big(\mathbb{E}_t\big[\pi_{t+1}\big] - \pi^T\big) + \gamma\big(\mathbb{E}_t\big[y_{t+1}\big] - y^e\big) \tag{4}$$

In addition, they also transform the nominal interest rate i_t into the *ex ante* real interest rate r_t by subtracting inflation expectations. With this transformation, the weight assigned to the deviation of inflation expectations from the target becomes $\beta - 1$. Finally, they also introduce an interest rate smoothing term, ρ. Goodfriend (1991) argues that this gradual adjustment occurs in order to avoid large turbulences or losses of credibility. This formulation, expressed by Equation (5), constitutes the baseline structure of reaction functions to this day.

$$r_t = (1-\rho)\Big[\bar{r} + (\beta - 1)\big(\mathbb{E}_t[\pi_{t+1}] - \pi^T\big) + \gamma\big(\mathbb{E}_t[y_{t+1}] - y^e\big)\Big] + \rho\, r_{t-1} \tag{5}$$

On the econometric side, there are challenges associated with estimating two main variables, the first of which is the output gap. The two fundamental families of estimators are: (1) statistical filters, such as those of Hodrick and Prescott (1997), Baxter and King (1999), and Christiano and Fitzgerald (2003), which extract a trend; and (2) production function approaches based on available supply-side factors such as capital, labor, and productivity. The first approach is problematic because it does not incorporate actual production data, whereas the second addresses this issue but relies on more data and assumptions regarding the functional form.

Closely related to the challenge of estimating the output gap is the estimation of the neutral real interest rate. This rate, in turn, is unobservable and cannot be computed using the same trend filters. The seminal approach of Laubach and Williams (2003) treats it as an unobservable variable within a State-Space Model, estimating it jointly with the output gap via the Kalman filter. This is the most common technique for estimating the neutral real interest rate.

Turning to the estimation of the parameter associated with the weight assigned to the deviation of inflation from the target, β, there are also methodological variants. The starting point for the estimation of time-varying parameters in the monetary policy literature was provided by Cogley and Sargent (2001), who introduced the use of SSMs in this context. Although they did not directly estimate a Taylor Rule, their results showed that the relationships among inflation, output, and interest rates in the United States changed over the postwar period. One of the first studies to formalize the hypothesis that the parameter β could vary over time was Owyang and Ramey (2004), which employed a Markov-switching model to identify discrete changes in the Federal Reserve's reaction function. The study showed that the intensity of the response to inflation is not stable over time.

Subsequently, studies such as Boivin (2006) replaced the discrete regime-switching mechanism with continuous parameter dynamics. Estimation was carried out within a State-Space Model using the Kalman filter, which is currently the most common and accessible approach. All of these studies consolidated not only the most coherent estimation methods, but also the idea that the Federal Reserve's response to inflation is dynamic. Finally, Amarante (2012) and Carvalho and Muinhos (2022) replicate the same econometric method using similar Taylor Rules to estimate Bacen's β.

2.2 Asset pricing

2.2.1 From heuristics to risk premia

The history of asset pricing is, before being a mathematical construction, a trajectory of beliefs, intuitions, and heuristic practices, as noted by Goetzmann and Rouwenhorst (2005). From the organized markets of the Amsterdam Stock Exchange in the seventeenth century, through London and later New York, early traders sought to identify assets offering attractive returns by relying on commercial information, political connections, and even rumors of war and trade. These early speculators rarely possessed systematic analyses; instead, they operated based on judgment, experience, and informal networks.

The first conceptual milestone in the formalization of asset pricing was the work of Williams (1938), who proposed that the intrinsic value of an asset should be calculated based on the present value of expected future cash flows. This approach was later formalized by Gordon and Shapiro (1956) in the well-known dividend growth model. This model established a relationship between a stock's price, its expected dividends, and the rate of return required by investors. Around the same period, modern portfolio theory emerged, pioneered by Markowitz (1952). He formally introduced the concept of optimal diversification and modeled risk as the variance of returns.

As markets matured, certain approaches began to stand out for their consistency. One of the most influential was so-called value investing, consolidated in the twentieth century by Benjamin Graham and popularized by his most famous disciple, Warren Buffett. This school held that markets frequently misprice assets, allowing the patient investor to purchase undervalued assets – below their estimated intrinsic value. Firm valuation was based on accounting multiples, earnings history, and often governance considerations; a conservative management approach with a long-term horizon. Buffett's famous metaphor of buying one dollar for fifty cents encapsulates this reasoning. With his sober style and extreme discipline, Buffett transformed this philosophy into one of the most enduring traditions in asset management. The central idea is that it was possible to consistently beat the market through common sense, discipline, and fundamental analysis.

While Graham and Buffett exploited temporary price deviations relative to value, another strand emerged from a different question: which risks do assets carry that the market systematically rewards? This perspective arose with the development of risk-return models and would give rise to what came to be known as factor investing. The core idea is that certain systematic risk factors – such as market exposure – consistently generate premia. That is, unlike classical value investing, factor investing is based on the premise that superior returns arise from exposure to systematic risks.

Thus, the trajectory of asset pricing follows a path that moves from the informal intuition of early traders, to the fundamentalist rationality of accounting-based analysts, and ultimately to the statistical rigor of factor investors. Each phase reflects not only advances in theory, but also technological and informational transformations. The work of Markowitz (1952), in particular, was decisive in introducing the idea that portfolios can be optimized and that idiosyncratic risk is diversifiable. The focus of statistical studies then shifted to systematic risk, creating the need to understand it, identify it, and study how it translates into expected returns.

2.2.2 The systematic risk factors

The first formal risk premium factor was proposed by Sharpe (1964), Lintner (1965), and Mossin (1966) in the Capital Asset Pricing Model (CAPM). The CAPM – Equation (6) – established that an asset's expected return should be proportional to its systematic risk, measured by its beta with respect to the market portfolio. This formulation was pioneering and innovative in introducing the concept of non-diversifiable risk.

$$\mathbb{E}(R_i) = R_f + \beta_i\big(\mathbb{E}(R_m) - R_f\big) \tag{6}$$

The central idea is that firms more exposed to the market earn higher returns, but also bear greater systematic risk. In theory, higher returns cannot be achieved without greater exposure and risk. The CAPM goes beyond a theory of returns; it is also a model of market efficiency. In a monumental review of the literature, Fama (1970) consolidates this view by formalizing the EMH, showing that the CAPM is consistent with an environment in which prices reflect all available information. In this context, returns above those predicted by systematic risk – represented by a significant intercept – would merely be transitory deviations, rather than systematic profit opportunities.

Subsequently, Black et al. (1972) and Fama and MacBeth (1973) tested the CAPM and found evidence that, although there is a relationship between the market and individual assets, this relationship is insufficient to explain the cross section of returns. The work of Fama and MacBeth (1973) is also particularly relevant for proposing the benchmark method for estimating risk premia still used today: the Fama-MacBeth regression. In this context, the Arbitrage Pricing Theory (APT) of Ross (1976) emerged. The APT allowed multiple factors to explain returns, provided that these factors did not generate arbitrage opportunities. Unlike the CAPM, the APT did not specify which factors were relevant, opening the door for the literature to empirically identify the factors that explain returns.

In the subsequent years, Banz (1981) identified the size effect, associated with the superior performance of smaller firms. Meanwhile, Stattman (1980) and Rosenberg et al. (1985) documented the value effect, related to higher returns for stocks with high book-to-market ratios. Chen et al. (1986) were also influential in testing macroeconomic factors as sources of systematic risk. This movement marked the emergence of macro-factors in the asset pricing literature, linking real economic variables to the behavior of financial markets.

The evidence accumulated throughout the 1970s and 1980s suggested that the prevailing asset pricing model was incomplete and that the market factor did not capture all of the systematic risk to which an asset is exposed. This view culminated in Fama and French (1993), who formulated the Three-Factor Model by incorporating two additional factors into the CAPM: firm size and value. The authors constructed two portfolios representing, respectively, small firms and firms with high book-to-market ratios. These portfolios were called Small Minus Big (SMB) and High Minus Low (HML), and were designed to mimic these presumed common sources of market risk – size risk and value risk. Each stock's exposure to these risks represents a source of non-diversifiable risk to which the asset is exposed in order to earn higher returns. A stock with low market capitalization tends to – but does not necessarily – exhibit high sensitivity to the SMB factor, which increases its exposure to this systematic risk and helps explain part of its superior returns.

In the following decades, there was a true explosion in the number of factors identified in the literature. In response, studies such as Green et al. (2017) sought to identify, among dozens of firm-specific factors, those that truly provide independent and robust information about average stock returns. The authors conclude that only a very small fraction of these factors exhibits stable statistical significance over time, reinforcing the need for greater empirical rigor in the selection of relevant factors in multifactor models.

Among the many factors identified over recent decades, five stand out. Jegadeesh and Titman (1993) discovered the pattern that stocks with strong recent performance tend to continue performing well in the short run. Carhart (1997) formalized this premium by constructing and testing the momentum (MOM) factor portfolio. Following the same mimicking portfolio construction approach, Amihud (2002) introduced the liquidity factor – illiquid assets earn higher returns – and Novy-Marx (2013) the profitability factor – firms with high profit generation sustain higher returns. Titman et al. (2004) identified the investment effect, indicating a risk premium for firms that reinvest less in their assets. This occurs because firms that invest little typically do so because they operate in sectors or periods characterized by greater uncertainty and risk.

Subsequently, Fama and French (2015) returned to the forefront and expanded the Three-Factor Model into the Five-Factor Model by incorporating the previously documented profitability and investment factors, termed Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA), respectively. Finally, more recently, Asness et al. (2017) proposed the quality factor, which combines several dimensions of financial soundness – such as earnings stability, low leverage, and good governance practices – to capture the relatively superior performance of financially robust firms. This factor was termed Quality Minus Junk.

In parallel, studies on macroeconomic factors developed at a slower pace, in part due to the relatively lower abundance of macroeconomic variables compared to firm-specific ones. The seminal contribution in this strand is the study by Chen et al. (1986), which tests whether innovations in macro variables – such as industrial production, inflation, and interest rate and credit spreads – constitute sources of risk priced by the market. They find evidence that stocks' exposure to these macroeconomic shocks is rewarded. In other words, there exists a risk premium for exposure to macroeconomic factors.

The next step in this agenda was the incorporation of monetary policy components as determinants of risk premia. Patelis (1997) show that monetary policy variables are significant predictors of return dynamics. Meanwhile, Bernanke and Kuttner (2005) demonstrate that surprises in Federal Reserve decisions produce immediate revaluations of stock prices, evidencing assets' exposure to monetary policy. More recently, Ozdagli and Velikov (2016) constructed an index of exposure to monetary policy shocks and estimated its relationship with stock returns. They found that assets with greater exposure to monetary policy exhibit lower average returns.

Another notable contribution is Lettau and Ludvigson (2001), who integrated the consumption-wealth ratio as a predictor of stock returns. In the fiscal domain, the study by Sialm (2009) provided one of the theoretical foundations for understanding fiscal policy as a source of systematic risk in financial markets. The author shows that changes in taxes on dividends and capital gains directly affect asset pricing, demonstrating that the tax burden – and thus fiscal policy – is incorporated into expected returns. Building on the identification of this effect, Da et al. (2018) conducted one of the first empirical studies to estimate a fiscal risk premium. They analyzed how stocks' exposure to variations in fiscal policy across U.S. states translates into differences in expected returns. These studies established fiscal policy as a relevant macroeconomic risk factor in the asset pricing literature.

In sum, the line of research on macroeconomic factors has evolved from the use of simple market variables to the use of constructed indices with more sophisticated interpretation and theoretical grounding. Examples include the consumption-wealth ratio and exposure to monetary and fiscal policy. Thus, this macroeconomic strand in asset pricing has become consolidated as a complementary branch to the firm-specific factor literature, providing alternative explanations with valuable economic interpretations. Today, the set of models leads to a theoretical consensus regarding the determinants of an asset's expected return.

$$\mathbb{E}_t\big(R^i_{t+1}\big) = f\left(\sum_k \lambda_{k,t+1}\,\beta_{i,k};\sum_{l=1}^{L}\theta_i\,C_{i,l};\alpha_i\right) \tag{7}$$

As shown in Equation (7), the first term relates to factors: exposures to risks that have historically compensated investors. The second term refers to characteristics of groups of assets that may affect returns through biases. The third term stems from traditional firm valuation models; it reflects the valuation attributed to a stock based on financial fundamentals.

In the literature, there is an ongoing debate over whether certain aspects are characteristics or factors; that is, whether they represent a risk premium or a mispricing due to cognitive biases. The distinction is subtle, but its interpretation and economic reasoning are far from trivial. Firm size, for instance, can be interpreted as a risk factor that earns a premium. Under this perspective, returns associated with size arise purely from risk exposure. An alternative interpretation is that size may be a characteristic that generates bias, artificially increasing or decreasing returns through beliefs about groups of assets. A similar discussion applies to firm quality. Do financially robust firms bear systematic risks that make them riskier and therefore more profitable? Or is there a bias in favor of low-quality stocks that makes healthy firms relatively underpriced? This is an ongoing debate that defines different schools of thought. Fortunately, with respect to macroeconomic factors, there is less ambiguity. They are fundamentally systematic, and their primary channel affecting expected returns is through risk premia.

2.3 The exposure of firms to the Central Bank's stance

Taylor Rules and their development over time have theoretically modeled the behavior of central banks. Estimating these equations led to the identification of time-varying parameters, including the parameter related to the central bank's stance, β. Meanwhile, the development of multifactor asset pricing models opened the door to empirically testing hundreds of factors – both macroeconomic and firm-specific – based on their theoretical effects on returns. No prominent study has explicitly tested or identified the empirical or theoretical effect of the parameter β – the degree of the central bank's concern with inflation – on returns. Nevertheless, this effect has been explored in a diffuse manner at each stage of the causal chain.

A large body of academic work investigates how a central bank's stance affects different macroeconomic and financial variables. Gürkaynak et al. (2005) show that central bank reactions and communication anticipate changes in the yield curve and long-term interest rates. They find that a central bank more concerned with inflation tends to reduce inflation expectations and long-term interest rates, which is logically intuitive. Gilchrist and Zakrajšek (2012) and Bernanke et al. (1999) explain that, on average, credit conditions tighten under a monetary policy regime that is less permissive toward inflation. That is, corporate credit spreads increase and credit supply contracts. In sum, there is both theoretical and empirical support for the idea that the central bank's stance affects variables such as inflation expectations, long-term interest rates, credit spreads, and credit conditions themselves – all of which are frequently connected to stock returns.

The literature linking these variables to firms documents that the effects are not homogeneous; that is, different firms respond differently to changes in these intermediate variables. Campbell and Shiller (1988, 1998) show that variations in expected returns and discount rates explain a large share of stock price volatility, implying that changes in inflation expectations or long-term interest rates may affect assets with more distant cash flows more strongly. In turn, Bernanke et al. (1996) empirically demonstrate that firms with weaker balance sheets – more dependent on external financing – exhibit returns that are more sensitive to credit conditions. Therefore, the literature establishes that firm returns, in addition to being associated with inflation expectations, long-term interest rates, and credit conditions, are also associated with these variables with differing intensities across firms.

Bringing together all of these contributions, we arrive at a theoretical foundation for the proposed effect: (1) the monetary policy stance – assigning more or less weight to inflation in the interest rate decision – alters intermediate variables that are relevant for firms; and (2) these variables influence firm valuation and returns in a heterogeneous manner. Consequently, depending on firm characteristics such as cash flow duration, leverage, and debt maturity, a more accommodative central bank has a different impact on returns. This occurs through inflation expectations, long-term interest rates, and credit conditions.

In this sense, what has not yet been established is whether there is evidence that firms' exposure to the monetary policy stance is systematically compensated. Seeking to contribute to the literature, this study examines whether exposure to the central bank's stance – thus far not directly explored in previous studies – constitutes a source of systematic risk with an associated premium. On the one hand, identifying an additional relevant factor may broaden the understanding of the determinants of returns in the Brazilian market and offer new perspectives for portfolio management, thereby contributing additional explanatory power in a constantly evolving financial market. On the other hand, if the factor proves to be insignificant, the results are still valuable by delineating the scope of known factors and indicating that research and practical efforts may be better directed toward other dimensions of risk.

3 Methodology

3.1 Theoretical model

The theoretical model used in the central bank reaction function analysis is that proposed by Clarida et al. (1998), which is widely employed in the literature. The model follows Equation (8), where r_t is the *ex ante* real interest rate, $\bar{r}_t$ is the economy's neutral real interest rate, $\mathbb{E}[\pi_t]$ denotes expected inflation, π_t^T is the inflation target, $\tilde{y}_t$ is the output gap, ρ is Bacen's interest rate smoothing parameter, γ is the parameter associated with the weight placed on activity imbalances, and β_t is the parameter associated with the weight placed on inflation deviations.

$$r_t = (1-\rho)\Big(\bar{r}_t + (\beta_t - 1)\big(\mathbb{E}[\pi_t] - \pi_t^T\big) + \gamma\,\tilde{y}_t\Big) + \rho\, r_{t-1} \tag{8}$$

Support variables, such as the exchange rate or fiscal policy, were not included for several reasons. The former is directly connected to Bacen's objective. Article 1 of Complementary Law No. 179, of February 24, 2021[1], which provides for the autonomy of the Central Bank of Brazil, establishes that (author's translation)[2]:

> The Central Bank of Brazil has as its fundamental objective to ensure price stability. [...] Without prejudice to its fundamental objective, the Central Bank of Brazil also aims to safeguard the stability and efficiency of the financial system, smooth fluctuations in the level of economic activity, and foster full employment.

Therefore, one should not expect policy actions to be based purely on the prevailing exchange rate. Naturally, as explored in the literature by Dornbusch (1980) and Krugman (1987), the exchange rate affects inflation and may trigger a response by Bacen. However, any potential pass-through effect should be captured by inflation expectations, making the inclusion of an additional variable unnecessary. Finally, although the model is not identical to that of Clarida et al. (1998) – in the sense that it does not use output gap

[1]Complementary Law No. 179, of February 24, 2021. *Diário Oficial da União*, Brasília, DF, Feb. 25, 2021.

[2]O Banco Central do Brasil tem por objetivo fundamental assegurar a estabilidade de preços. [...] Sem prejuízo de seu objetivo fundamental, o Banco Central do Brasil também tem por objetivos zelar pela estabilidade e pela eficiência do sistema financeiro, suavizar as flutuações do nível de atividade econômica e fomentar o pleno emprego.

expectations – it is expected that fiscal policy effects are captured by the current output gap, also rendering the inclusion of a fiscal policy proxy unnecessary.

The multifactor asset pricing theoretical model adopted is based on the framework of Gürkaynak et al. (2005), Gilchrist and Zakrajšek (2012), Bernanke et al. (1996, 1999), and Campbell and Shiller (1988, 1998). As detailed in the previous section, these studies establish that the central bank's stance affects inflation expectations and long-term interest rates, as well as credit conditions. These, in turn, affect asset returns heterogeneously, depending on characteristics such as cash flow duration, leverage, and debt maturity. As such, these works establish a theoretical link between the central bank's stance and asset returns. The mathematical formalization of this theoretical model is based on the APT proposed by Ross (1976), as shown in Equation (9). In it, the expected return of asset i, $\mathbb{E}[R_i]$, depends linearly on its exposure, θ_i, to the central bank's preference, β_t, plus a set of n relevant systematic risk factors, f.

$$\mathbb{E}[R_i] = \theta_{i,\beta}\,\beta_t + \sum_n \theta_{i,f_n}\,f_n \tag{9}$$

In this context, it is proposed that asset i's exposure to the monetary authority's preferences constitutes an additional priced systematic risk factor. Therefore, by hypothesis, there exists a risk premium associated with a stock's sensitivity to this variable. Accordingly, the expected return is a linear function of β_t and other relevant factors, f_n.

3.2 Econometric model

In order to estimate the time-varying series of the parameter associated with Bacen's preferences, a linear Gaussian State-Space Model is employed. Its general form includes a measurement equation, Equation (10), and a state equation, Equation (11).

$$r_t = (1-\rho)\Big(\bar{r}_t + (\beta_t - 1)\big(\mathbb{E}[\pi_t] - \pi_t^T\big) + \gamma\,\tilde{y}_t\Big) + \rho\,r_{t-1} + \varepsilon_t \tag{10}$$

$$\beta_t = \beta_{t-1} + \eta_t \tag{11}$$

$$\varepsilon_t \sim \mathcal{N}\big(0, \sigma_\varepsilon^2\big)\,, \qquad \eta_t \sim \mathcal{N}\big(0, \sigma_\eta^2\big) \tag{12}$$

In this framework, r_t, $\bar{r}_t$, $\mathbb{E}[\pi_t]$, π_t^T, and $\tilde{y}_t$ are observable variables, ρ and γ are latent variables, and β_t is the state variable. In addition, as shown in Equation (12), ε_t and

η_t are Gaussian white noise terms. The model is estimated using Maximum Likelihood Estimation via the Kalman filter. In order to provide initial guesses for the state variable, Equation (10) is first estimated with β assumed to be constant over time. This is done using the Nonlinear Least Squares estimator, employing the iterative Levenberg-Marquardt method proposed by Marquardt (1963).

Having done so, the estimated time series $\hat{\beta}_t$ is incorporated as a factor, together with other control factors, into one of the most widely used models in the literature for estimating risk premia: the Fama-MacBeth regression proposed by Fama and MacBeth (1973). In addition, four different approaches are estimated, each including a different set of control factors. In the first, the risk premium associated with $\hat{\beta}$ is estimated jointly with the CAPM market factor and a constant. In the second, the size and value factors – SMB and HML – are included, completing the three factors of Fama and French (1993). The third approach includes the investment and profitability factors – CMA and RMW – completing the model of Fama and French (2015). In the last, the momentum factor of Jegadeesh and Titman (1993) is included. The four approaches are labeled, respectively, CAPM, FF3, FF5, and FF5+Mom. These factors are chosen because they are the most extensively studied and enjoy the strongest empirical support. Moreover, their inclusion is common practice in the literature. Ribeiro et al. (2024), for example, include exactly these variations in an analysis of the impact of firm characteristics on returns.

Turning to the econometric model itself, the first step is to estimate, for each asset, a time series regression using Ordinary Least Squares (OLS). In this regression, the asset's return is regressed on the proposed factor $\hat{\beta}$ and on the control factors. Equation (13) illustrates the regression for the FF3 approach. The coefficients $\hat{b}$ capture each stock's exposure to each factor.

$$R_t = b_0 + b_1\hat{\beta}_t + b_2\,\mathrm{MKT}_t + b_3\,\mathrm{SMB}_t + b_4\,\mathrm{HML}_t + \varepsilon_t \tag{13}$$

It is worth noting that the coefficients $\hat{b}$ are re-estimated every year. Thus, every four quarters Equation (13) incorporates new observations and yields a new set of coefficient estimates. The sample length used in the first estimation depends on the chosen approach, such that a minimum number of observations – equal to the square of the number of regressors – is satisfied. That is, under the FF3 specification, the minimum number of observations is 25. Therefore, the first estimation uses the first 25 quarters of data. The second uses the first 29 quarters, and so on. This design is part of the methodology proposed by Fama and MacBeth (1973).

The second stage of the model consists of using the coefficients $\hat{b}$ as explanatory variables for the returns of the corresponding assets at each point in time. Thus, in the FF3 example, Equation (14) is estimated in cross section via OLS for each time period. Note that the subscript t does not indicate the use of time series variables; it is included to denote that asset returns in period t are regressed on the exposures from period $t-1$. Therefore, the explanatory variables in Equation (14) contain data that were not used in estimating the regressors $\hat{b}$. Moreover, as suggested by Fama and MacBeth (1973), for additional interpretation, the sample standard deviation of the residuals from Equation (13) is included. This variable serves as an estimate of idiosyncratic risk, that is, the risk not explained by factor exposures. The coefficients $\hat{\lambda}$ capture the sensitivity of returns to the asset's exposure to each factor.

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}\,\hat{b}_{1,i,t-1} + \lambda_{2,t}\,\hat{b}_{2,i,t-1} + \lambda_{3,t}\,\hat{b}_{3,i,t-1} + \lambda_{4,t}\,\hat{b}_{4,i,t-1} + \lambda_{5,t}\,\hat{s}_{\varepsilon_{i,t-1}} + \epsilon_{i,t} \tag{14}$$

Additionally, as shown in Equation (15), the mean of the coefficients $\hat{\lambda}_{t,i}$ yields the risk premium associated with factor i. We can also use these estimates to compute the standard error of $\bar{\hat{\lambda}}i$. As shown in Equation (16), this is simply the sample standard deviation of $\hat{\lambda}t, i$ adjusted for the sample size.

$$\bar{\hat{\lambda}}_i = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{t,i} \tag{15}$$

$$s_{\bar{\hat{\lambda}}_i} = \frac{s_{\hat{\lambda}_{t,i}}}{\sqrt{T}} \tag{16}$$

$$t_{\bar{\hat{\lambda}}_i} = \frac{\bar{\hat{\lambda}}_i}{s_{\hat{\lambda}_i}/\sqrt{T-1}} \tag{17}$$

Finally, the computed data can be readily used in Equation (17) to calculate the t-statistic for hypothesis testing. This is particularly useful for conducting inference and arriving at reliable and interpretable results. Fama and MacBeth (1973) also warn of evidence that stock return distributions exhibit fat tails relative to the normal distribution. For this reason, and in line with academic practice, the test is conducted using a two-tailed Student's t-distribution.

3.3 Data

For the first stage of this study, data on economic activity, interest rates, and inflation are used, all at a quarterly frequency. The output gap and neutral real interest rate data are estimated and periodically published by Bacen in the Monetary Policy Reports (RPM). Since the objective of this study is not to model these series, the official Bacen estimates are used, as they result from more sophisticated and robust models than could be developed here without excessively expanding the scope of the analysis. Specifically, for the output gap, the reference scenario series is adopted, and for the neutral interest rate, the arithmetic average of the reported estimates is used. For the inflation expectations series, 12-month-ahead expectations published in the Focus Market Report are collected.

Finally, *ex ante* real interest rate data are constructed from the quarterly accumulated Selic rate, annualized, and the 12-month-ahead inflation expectation. The natural logarithm of the Selic rate is subtracted from the natural logarithm of expected inflation. The selected sample period runs from the second quarter of 2005 to the first quarter of 2024 – exactly 19 years, or 76 quarters. The sample cutoff is determined by the availability of neutral real interest rate data.

For the second stage of the study, daily stock return data adjusted for dividends and other distributions are collected for all stocks traded on B3. The sample includes both firms that are no longer listed and firms that were not listed in 2005. Firms with duplicated CNPJ identifiers are excluded, and in cases where a company has both preferred and common shares, only the share class with the highest market capitalization is retained. This procedure is adopted to equalize the weight of each firm's effect, since no market-capitalization weighting is applied in this analysis. To transform daily data into quarterly frequency, cumulative returns are calculated for each asset within each quarter. The final number of firms included in the sample is 683.

This return dataset also underwent meticulous preprocessing. First, for each firm, returns were winsorized at 5% – values below the 5th percentile or above the 95th percentile were replaced by the respective threshold values. Second, for each estimation of Equation (14), firms that did not meet the minimum data requirement – equal to the square of the number of regressors – were excluded. Third and finally, if the estimation of Equation (14) resulted in residuals exhibiting serial correlation or heteroskedasticity, the firm was also discarded from that estimation round. The tests employed were the Ljung-

Box and White tests – Ljung and Box (1978) and White (1980) – using the conventional 5% significance level.

The CAPM market factor used is the quarterly return of the Bovespa stock index. The other five factors mentioned are portfolios calculated and published on Kenneth French's website. However, these are constructed for the U.S. equity market. Fortunately, as part of their study on firm characteristics and returns in Brazil, Ribeiro et al. (2024) construct portfolios analogous to the factors of Fama and French (2015) and Carhart (1997) using Brazilian stocks. They provide monthly returns for more than 24 factors, which are aggregated to quarterly frequency based on cumulative returns within each quarter.

4 Results

This section is divided into four parts. First, preparatory steps for the model are carried out, including the plotting of key time series, several unit root tests, and the estimation of initial guesses for the SSM. The following subsection presents the estimations and interpretation of the results. The final two subsections contain the tests required to validate the underlying assumptions, as well as a monthly estimation of the model for the purpose of robustness checks.

4.1 State-Space Model preparation

As mentioned earlier, the output gap used was the one estimated and published by Bacen. This series, in principle, removes the GDP trend and fluctuates around zero. Therefore, it is not expected to contain a unit root. Even so, the Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981) was performed. The result, reported in Table 12 of Appendix A, allowed for the rejection of the null hypothesis of a unit root at significance levels greater than 5%, but not at levels greater than 1%.

From its time series, shown in Figure 1, it is possible to identify several historical events in the Brazilian economy, e.g. the sharp decline in the third quarter of 2008 that kept the output gap negative until the first quarter of 2009. This shock was the global financial crisis, which originated in the United States with the collapse of the housing market, spread through vulnerabilities in the U.S. financial system, and reached a global scale by weakening one of the world's main centers of demand.

Brazil's rapid recovery after the financial crisis leads to the next period: a phase of strong fiscal stimulus and a positive output gap from 2010 to mid-2014. This cycle ended only with a major fiscal consolidation and a contractionary monetary policy aimed at containing inflation. Thus, between 2015 and 2017, Brazil experienced significant declines in output, followed by a very slow and gradual recovery from 2017 to 2019. Before the output gap could even turn positive, the COVID-19 pandemic in 2020 caused a sudden drop of 5 percentage points. Nevertheless, one year later the economy had already returned to levels similar to those observed prior to the pandemic. Finally, since 2022, Brazil has been in a phase of a positive output gap – something that last occurred in 2015.

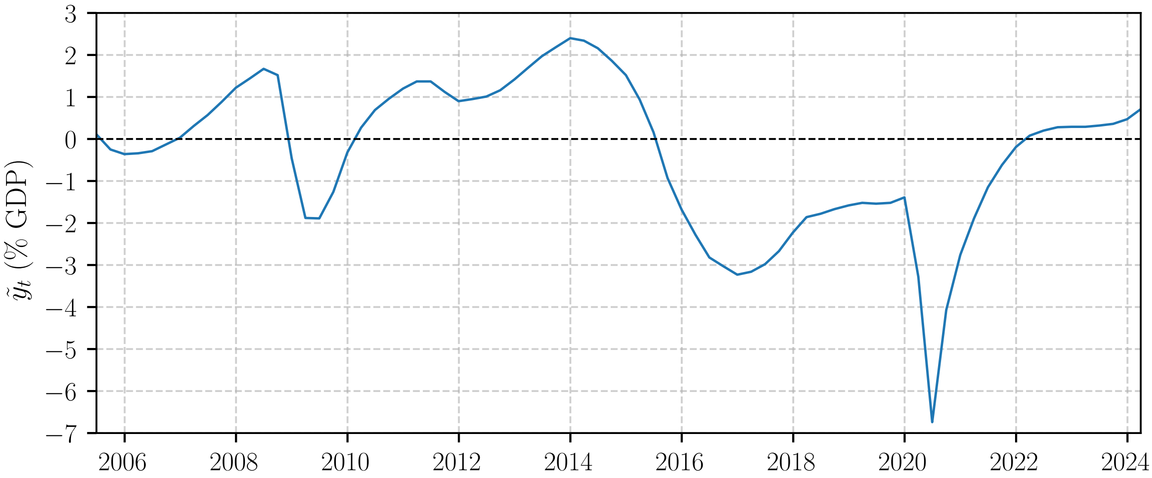


Figure 1: Output gap estimated by the Central Bank of Brazil

The next figure presents a series that is highly relevant for describing Bacen's stance. Figure 2 shows the inflation target and its tolerance bands over time, along with 12-month-ahead inflation expectations. We observe that, for most of the period, expectations were close to the upper band of the target. Moreover, on three occasions they exceeded it: in the first and last quarters of 2015, the first quarter of 2016, and from the fourth quarter of 2021 to the second quarter of 2022. Expectations were also at the lower band only three times. Altogether, this evidence points to an upward inflation bias, in which the center of the target does not appear to be fully credible.

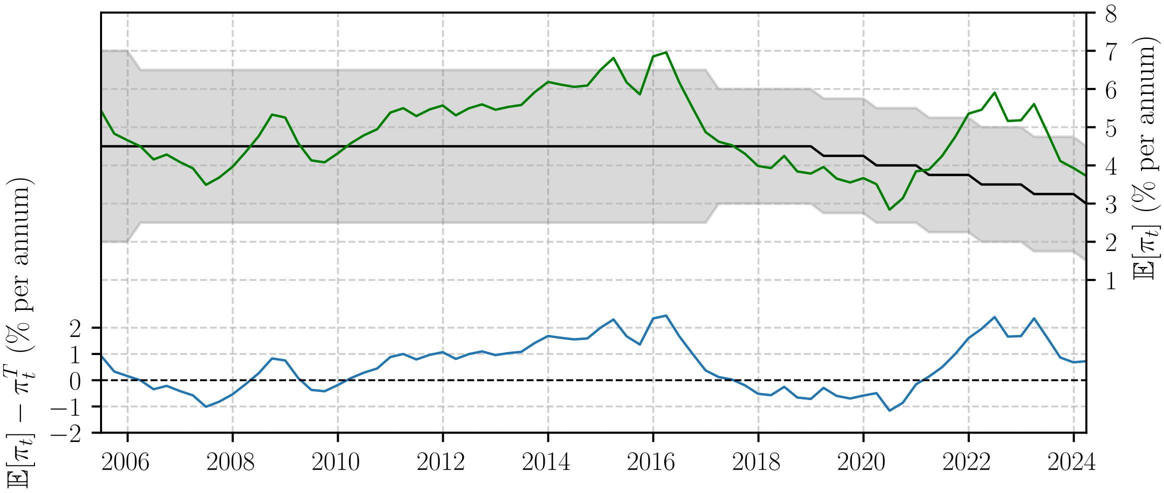


Figure 2: Inflation target and expectations over time

The ADF test on the deviation of inflation expectations – Table 1 – led to a failure to reject the null hypothesis of a unit root at any conventional level of statistical significance. Therefore, the series is nonstationary and exhibits a stochastic trend. That is, shocks are not temporary, and deviations in expectations display high inertia and do not revert to an equilibrium level. This outcome is undesirable under an inflation-targeting regime and indicates a lack of control by Bacen. Ultimately, it implies that inflation expectations were, on average, not anchored over this period.

Table 1: ADF test on the deviation of inflation expectations from the target

Observations	73	t-statistic	p-value
Augmented Dickey-Fuller test statistic		-2.57971	0.29065
Critical test values:	1% level	-4.0906	
	5% level	-3.47345	
	10% level	-3.16397	

The next series – Figure 3 – was also extracted from Bacen's models: the estimate of the neutral real interest rate. It exhibits a steady decline from 2006 until mid-2020, reflecting structural transformations in the economy possibly associated with the maturation of the financial market and changes in saving behavior. Nevertheless, this downward trend was reversed starting with the 2020 pandemic, with the neutral rate increasing by nearly 2 percentage points since then.

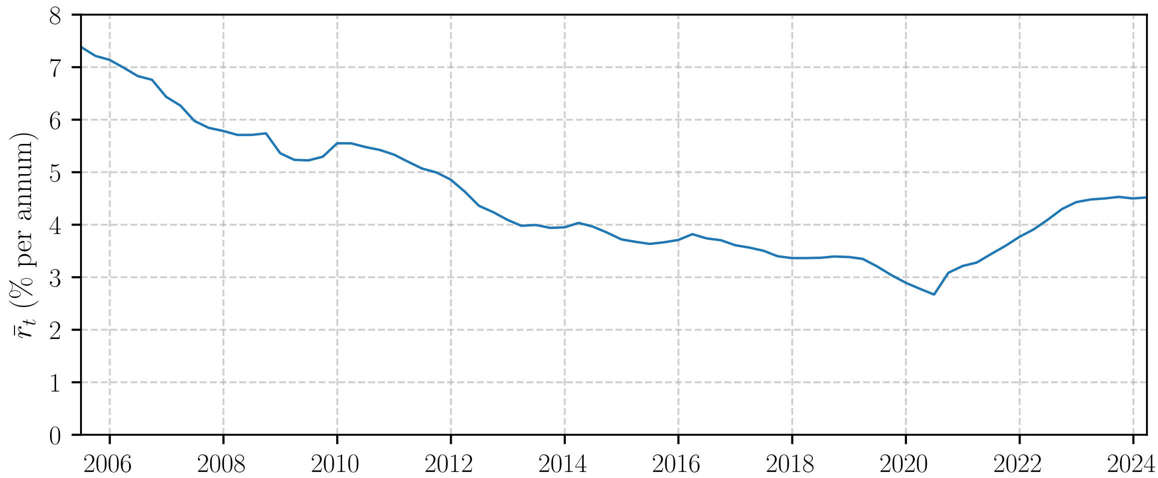


Figure 3: Neutral real interest rate estimated by the Central Bank of Brazil

The unit root test on this series, as shown in Table 2, yields a high p-value, leading to a failure to reject the null hypothesis of a unit root. In addition, the estimated trend term in the ADF test equation reported in Table 3 also exhibits a high p-value. Therefore, despite the visual impression, the neutral real interest rate does not exhibit a deterministic trend.

In economic terms, it is not governed by temporary shocks around a constant; rather, it evolves according to a stochastic trend driven by the economy's structural characteristics.

Table 2: ADF test on the neutral real interest rate

Observations	75	t-statistic	p-value
Augmented Dickey-Fuller test statistic		-0.63547	0.97372
Critical test values:	1% level	-4.08688	
	5% level	-3.47169	
	10% level	-3.16295	

Table 3: ADF test equation on the neutral real interest rate

Variable	Estimated value	Standard error	t-statistic	p-value
$\bar{r}_{t-1}$	-0.01187	0.01867	-0.63547	0.5272
$\Delta\bar{r}_{t-1}$	0.42682	0.11093	3.84758	0.00026
intercept	-0.01502	0.12173	-0.12339	0.90215
trend	0.00125	0.00110	1.13227	0.26138

Finally, Table 4 presents the results from estimating Equation (13) using Nonlinear Least Squares. The first highlight concerns the value of $\hat{\rho}$ – the inertia or smoothing of the interest rate chosen by Bacen. The value of 0.89 is statistically significant and indicates that the interest rate decision rule affects only 11% of the newly chosen rate. The remaining 89% is determined by the previous rate, with the objective of avoiding abrupt changes.

Table 4: Nonlinear Least Squares initial estimation

Coefficient	Estimated value	Standard error	z-statistic	p-value
$\hat{\rho}$	0.88694	0.0323	27.45536	0
$\hat{\beta}$	4.20209	1.0482	4.00887	0.00015
$\hat{\gamma}$	0.54432	0.50537	1.07706	0.28505
Observations	76	Durbin-Watson statistic		0.94685
R-squared	0.94765	Dependent variable mean		5.25098
Adjusted R-squared	0.9462	Dependent variable standard deviation		3.3016
Regression standard error	0.76581	Akaike Information Criterion		2.34341
Residual sum of squares	42.22518	Schwarz Information Criterion		2.43611
Log-likelihood	-84.87771	Hannan-Quinn Information Criterion		2.38042

Second, the estimated $\hat{\beta}$ is statistically significant and indicates that a one percentage point deviation of inflation expectations from the target has an effect of 3.2 percentage points on the optimal real interest rate. Taking the estimate of $\hat{\rho}$ into account, we can say that inflation expectations that are unanchored by one positive percentage point lead, on average, to an increase of 0.36 percentage points in the real interest rate chosen by Bacen. Finally, the estimate of $\hat{\gamma}$ is not statistically significant at any conventional significance level. That is, on average, Bacen does not take the output gap into account when setting interest rates. Despite this interpretation, all of these results are preliminary and are used solely to provide initial estimates for the Kalman filter.

4.2 Estimation

4.2.1 The stance of the Brazilian Central Bank

Table 5 presents the estimates of the latent variables and the state variable in the final period. The residuals of the measurement equation and the state equation, $\hat{\sigma}\varepsilon$ and $\hat{\sigma}\eta$ respectively, exhibit statistically significant standard deviations. In the context of the model, $\hat{\sigma}_\eta$ being different from zero implies that $\hat{\beta}_t$ varies over time. In addition, the estimated value of $\hat{\rho}$ is very close to the initial estimate reported in Table 4, with a slightly higher value of 0.89.

Table 5: State-Space Model estimates

Coefficient	Estimated value	Standard error	z-statistic	p-value
$\hat{\sigma}_\varepsilon$	0.50046	0.06192	8.08232	0
$\hat{\sigma}_\eta$	3.55596	1.56261	2.27565	0.02287
$\hat{\rho}$	0.89404	0.03011	29.68902	0
$\hat{\gamma}$	1.52663	0.88281	1.72929	0.08376
	Final state	Root MSE	z-statistic	p-value
$\hat{\beta}$	-0.1894	5.45502	-0.03472	0.9723
Observations	76	Akaike Information Criterion		2.22814
Log-likelihood	-79.55512	Schwarz Information Criterion		2.35174
Parameters	4	Hannan-Quinn Information Criterion		2.27749

Another noteworthy result is the variable $\hat{\gamma}$, which – unlike in the initial estimation – was statistically significant at the 10% significance level in the SSM. The estimated value indicates that a one percentage point positive output gap increases Bacen's optimal real interest rate by 1.52 percentage points. Taking $\hat{\rho}$ into account, this output gap translates, on average, into an increase of 0.16 percentage points in the chosen real interest rate.

The final estimated value of $\hat{\beta}_t$ was not statistically significant at any conventional probability level. The interpretation is that, in the first quarter of 2024, the optimal real interest rate decreases by one percentage point for each percentage point by which inflation expectations exceed the target. Incorporating $\hat{\rho}$, this same inflation deviation leads to a reduction of 0.1 percentage points in the prevailing real interest rate. Such weak or negative responses of the interest rate to inflation are precisely what classify Bacen as accommodative, or not.

Figure 4 presents the smoothed series of $\hat{\beta}_t$ over the entire estimation period, highlighting the different Bacen presidents in office. Henrique Meirelles's tenure already exhibited values of $\hat{\beta}_t$ above the historical average through the end of 2007. During this period, the central bank stance parameter was around 7, indicating that a one percentage point deviation in expectations was met with an average increase of 0.74 percentage points in the real interest rate. From 2008 onward, the institution appears to have become much more stringent, reaching the second-highest level in the historical series of $\hat{\beta}_t$. At that time, a one percentage point deviation in expectations led to an average increase of 1.27 percentage points in the real interest rate. This period featured a brief cycle of aggressive monetary tightening, as shown in Figure 5, despite relatively moderate inflation deviations and a sharp decline in activity stemming from the global financial crisis. This episode defined one of the most rigid stances adopted by Bacen in the century. In the remaining years of Henrique Meirelles's tenure, the parameter gradually returned to its historical average value.

Alexandre Tombini's presidency began in 2011 with a period marked by sharp changes in Bacen's stance. From the time he took office until mid-2012, $\hat{\beta}_t$ fell from its historical average to the lowest value in the series, -9. This implies that a one percentage point increase in the deviation of expectations was met, on average, with a reduction of 0.95 percentage points in the real interest rate. Figure 5 illustrates this period of expansionary monetary policy, even in the presence of strong economic activity and accelerating expectations. This movement reflected, among other factors, the economic views of President Dilma Rousseff's administration, which advocated structurally lower interest rates and a greater role for public credit via state-owned banks. Tombini is understood to have partially yielded to political pressure, conducting an excessively expansionary monetary policy.

From 2013 onward, fiscal reforms and policy changes in Brazil allowed for a return to a less accommodative monetary policy stance. For three consecutive years, in response to unanchored expectations, there was no reduction in the prevailing real interest rate. The parameter $\hat{\beta}_t$ increased – initially through a sharp adjustment reflecting renewed concern with inflation, and subsequently more gradually until it returned to its historical average. During this period, a sharp drop in $\hat{\beta}_t$ in the last quarter of 2015 also stands out. This occurred due to a break in expectations regarding Dilma Rousseff's second term. Her administration began with the appointment of Joaquim Levy as Minister of Finance; however, over the course of the year, beliefs spread that fiscal adjustment would be only partial and that Dilma would not fully reverse her heterodox policies. This led to a sudden increase in inflation expectations and a decline in the *ex ante* real interest rate, as the tightening cycle had already ended. As a result, the theoretical model classifies this episode as a lenient monetary policy stance.

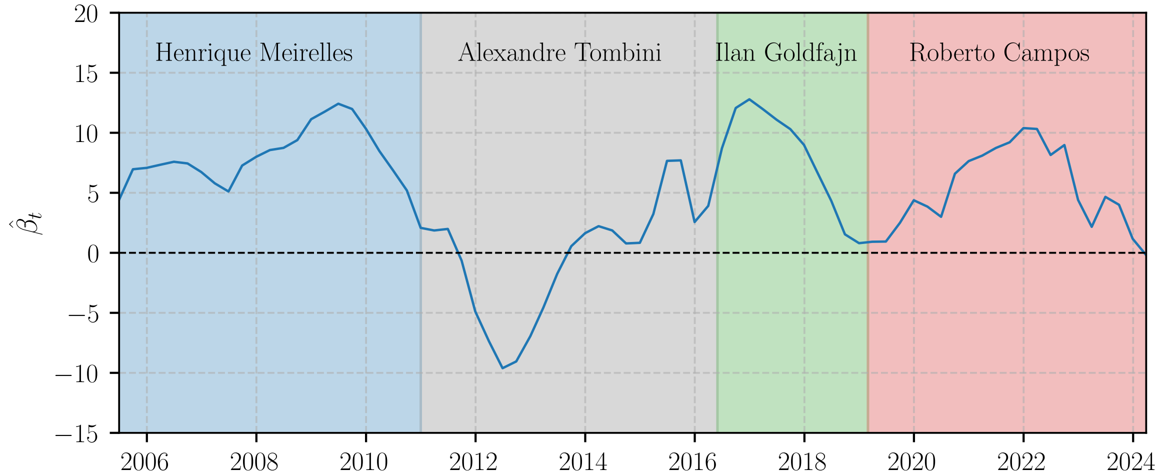


Figure 4: Brazilian Central Bank preferences, smoothed state variable

The next president, Ilan Goldfajn, took office in a context of declining expectations. As a result, even with interest rate cuts in the second half of 2016, the *ex ante* real interest rate increased for a brief period. This was sufficient to raise the parameter $\hat{\beta}_t$ to its historical maximum, 13. At that point, a one percentage point deviation in expectations led to an average increase of 1.37 percentage points in the real interest rate. During the remainder of his term, interest rates were only cut, and the parameter $\hat{\beta}_t$ declined almost continuously. Nevertheless, the former was not the cause of the latter. From 2018 onward, as shown in Figure 2, expectations were already below the target. In this sense, the Taylor Rule implies that the optimal decision would be to reduce the interest rate. Even so, 2018 was the year in which Bacen interrupted the easing cycle until the end of Goldfajn's term. Mathematically, this characterizes a central bank that does not assign substantial weight to deviations in expectations when setting interest rates; otherwise, it would have continued cutting rates. Therefore, the decline of $\hat{\beta}_t$ to values close to zero in 2019 does not imply that the central bank was unconcerned about high inflation. Rather, it reflects the fact that the model accounts for bidirectional deviations and that Bacen may have been sufficiently concerned about high inflation – given the loss of credibility in the previous decade – that the model was not fully suited to interpret this behavior.

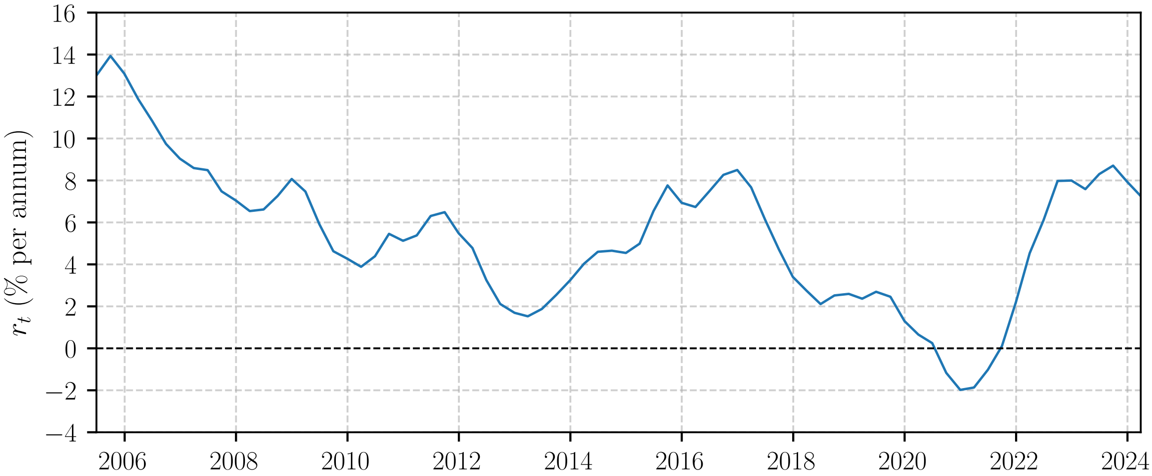


Figure 5: Real *ex ante* interest rate defined by the Central Bank of Brazil

The final president within the analysis window is Roberto Campos Neto, who took office at the beginning of 2019. From that point until the end of 2020, inflation expectations remained below the target, and Bacen finally implemented interest rate cuts – from late 2019 through the end of 2020 – leading to an episode of negative *ex ante* real interest rates. This interest rate response to a benign inflation environment was one of the factors contributing to the increase in $\hat{\beta}_t$, indicating that the central bank reacted to inflation. In subsequent years, starting in 2021, expectations accelerated and the most aggressive tightening cycle of the analysis period began. It consisted of approximately one year of consecutive rate hikes, which raised the real interest rate from around -2% to 8% per year by the second half of 2022. In the midst of this tightening cycle, in January 2022, the parameter $\hat{\beta}_t$ reached the third-highest value in the historical series, at around 10. At that point, a one percentage point positive deviation of inflation expectations translated, on average, into a one percentage point increase in the real interest rate.

After that, $\hat{\beta}_t$ declined steadily until returning to approximately zero at the beginning of 2024. In practical terms, inflation expectations were still above the upper band when the central bank halted the tightening cycle. Moreover, rate cuts began at the end of 2023, at a time when expectations were still nearly one percentage point above the target. All of this suggests, within the model, that Bacen was gradually assigning less importance to inflation, until in 2024 – by cutting rates even with expectations above the target – it effectively stopped responding to it altogether.

The economic interpretation of the series highlights its historical plausibility: $\hat{\beta}_t$ does indeed capture Bacen's behavior over recent decades. Nevertheless, model imperfections limit the use of $\hat{\beta}_t$ as a proxy for how agents perceive the central bank. One example is 2019, when the series exhibited a value classified as lenient despite the stance being clearly restrictive. This may constitute a limitation, since the theoretical link between Bacen's stance and asset returns operates through intermediate macroeconomic variables – such as inflation expectations, long-term interest rates, and credit spreads and conditions – which are affected by economic agents' perceptions of the central bank. If the model does not accurately capture this perception, a weak link arises in the theoretical framework. Fortunately, the only more pronounced case in which the model diverges from public perception is the trough between 2018 and 2021, a period that is relatively limited when compared to the full sample.

4.2.2 The risk premia for exposure

Table 6 summarizes all estimated risk premia. The first observation to note is that all estimates of $\bar{\hat{\lambda}}_0$ are statistically significant at the 1% significance level. The interpretation of this result is that, on average, there exists a return that is free of systematic risk in equities. One implication is that, if sufficiently relevant factors are included, the market is not efficient according to the EMH of Fama (1970), and it is possible to consistently obtain returns above those justified by exposure to systematic risks. Moreover, the estimated p-values indicate that, as more factors are incorporated, the probability that $\bar{\hat{\lambda}}_0$ remains significant decreases – that is, the likelihood that there exists a return unexplained by risk factors declines – which is economically intuitive.

Another interesting result concerns the estimate of $\bar{\bar{\lambda}}s\hat{\varepsilon}$, which captures the idiosyncratic risk premium – that is, the premium for firm-specific risk. As discussed by Fama and MacBeth (1973), an insignificant value of $\bar{\bar{\lambda}}s\hat{\varepsilon}$ implies that stocks' exposures to the selected factors constitute a complete measure of systematic risk. As shown in Table 6, the estimate of $\bar{\bar{\lambda}}s\hat{\varepsilon}$ is statistically significant for the CAPM at the 5% level. It is also significant for FF5+Mom at the 10% significance level. Thus, one may conclude that these specifications do not fully capture systematic risk. The fact that FF5 captures idiosyncratic risk whereas FF5+Mom does not appears to be an anomaly and may be explained by potential interference introduced by the momentum factor in the estimation of other risk premia. In addition, the sample sizes used to compute the means were 67, 51, 27, and 9 for the CAPM, FF3, FF5, and FF5+Mom approaches, respectively. Therefore, the latter has very low precision in its estimates. In terms of coefficient interpretation, for each unit of idiosyncratic risk – each unit of standard deviation of returns not explained by the model – there is a compensation of, respectively, 10.1% and -23% per quarter. Under the FF3 and FF5 specifications, these estimates are not statistically supported and become insignificant. The interpretation is that exposure to the market and to $\hat{\beta}_t$ alone does not constitute a complete measure of asset risk; however, once firm size, value, profitability, and investment are added, the set of factors becomes a sufficient measure of systematic risk.

Turning now to $\bar{\bar{\lambda}}MKT$, we initially observe a counterintuitive pattern. The estimate of this coefficient is negative. In the approaches where $\bar{\bar{\lambda}}MKT$ is statistically significant – CAPM at the 10% significance level and FF3 at the 5% significance level – the estimates are -0.017 and -0.03, respectively. Therefore, for each unit of exposure to the market, there is a negative premium of 1.7% and 3% per quarter; that is, a premium for low exposure. This result is related to the phenomenon documented by Frazzini and Pedersen (2014). The economic rationale lies in the leverage constraints faced by institutional investors, such as pension funds and mutual funds. Unable to increase their exposure to low-risk assets through borrowing, these agents invest more than usual in assets with high market exposure, inflating their prices and reducing their expected returns. Meanwhile, assets with low market exposure become undervalued and begin to offer higher returns. Despite this estimate being consistent with the literature, the $\bar{\bar{\lambda}}_{MKT}$ coefficients in FF5 and FF5+Mom are not statistically significant, indicating that the market exposure premium is absorbed and better explained by other systematic risk factors.

Estimates of the value premium are mixed, with an insignificant $\bar{\hat{\lambda}}_{HML}$ under the FF3 and FF5+Mom specifications. However, in FF5, the factor is statistically significant at the 1% significance level. This may occur because high-value firms also exhibit distinct investment and profitability patterns. Thus, when these factors are introduced in FF5, they act as controls, separating value risk from profitability and investment risk, thereby rendering the estimate significant. The estimate of 0.028 indicates a quarterly return premium of 2.8% per unit of exposure to HML. The investment factor also exhibits this heterogeneity. In FF5, it appears insignificant with a p-value of 13% and a negative sign. In FF5+Mom, however, it is statistically significant at the 5% significance level. Its value of -0.045 indicates a negative quarterly premium of 4.5% for each unit of exposure to CMA. Therefore, there is a risk premium associated with aggressive corporate investment, which is unexpected relative to the original theory but nonetheless understandable. Li and Chen (2022) analyze the Chinese stock market and find a similar result: firms that substantially increase their investment tend to exhibit higher returns.

The profitability factor, in turn, appears to exhibit greater consistency. The coefficient $\bar{\hat{\lambda}}RMW$ is statistically significant in both FF5 and FF5+Mom at the 5% significance level. The estimates indicate a negative premium of, respectively, 2.8% and 4.3% in quarterly returns per unit of exposure to RMW, showing that there is a premium associated with less profitable firms. The size risk premium, $\bar{\hat{\lambda}}SMB$, does not present a statistically significant value in any of the specifications. The disappearance of the size premium has already been identified and investigated internationally. Ahn et al. (2015) attribute the weakening of this factor to the fact that it is conditioned on the business cycle. They show that size premia are positive especially at business-cycle troughs. In turn, the prolonged duration of recent cycles causes this effect to appear less frequently and to dissipate. Moreover, the momentum factor, included only in FF5+Mom, also exhibits an insignificant estimate.

Finally, the estimates of $\bar{\hat{\lambda}}_{\hat{\beta}}$ are insignificant across all specifications, although in FF5 it presents a p-value of 15%. Its positive sign indicates that there is a premium for positive exposure to Bacen's stance. That is, there is a risk premium for firms that perform well when Bacen is austere. As highlighted in the theoretical framework, such periods are associated with low inflation expectations, lower long-term interest rates and spreads, and tighter credit conditions – periods of more moderate economic activity. By necessity, this premium would also be available to firms that perform poorly when Bacen is lenient. These are periods characterized by low inflation expectations, lower long-term interest rates and spreads, and abundant credit conditions – periods of stronger economic activity. Stocks with these characteristics are commonly referred to as countercyclical, as, broadly speaking, they perform well during recessions and poorly during expansions.

Bali et al. (2017) show that investors exhibit a preference for high-beta stocks with lottery-like characteristics, generally those that are more cyclical and volatile. This reduces the relative demand for countercyclical assets, leaving them undervalued and with higher expected returns – an argument similar to that of Frazzini and Pedersen (2014). Thus, the literature suggests that the premium associated with firms that are less sensitive to, or negatively related to, the business cycle stems from this generalized preference for more cyclical assets. This is a premium based on behavioral characteristics, not on systematic risk. Therefore, even if the estimate were statistically significant, one could not conclude that exposure to Bacen's preferences constitutes a source of systematic risk.

The estimated value of 1.25 indicates that, for each positive unit of exposure to β_t, there is a quarterly return of 125%. However, these numbers are not interpretable, since the scale of β_t is entirely different from the scale of factor returns – that is, replicable portfolios. Despite the interpretation being consistent with the literature, the p-value remains high, and therefore it is not possible to assert that there is a premium associated with exposure to Bacen's preferences. There are several possible reasons for this result. First, the theoretical foundation itself is diffuse and bundles multiple effects into a single measure. Within firms' exposure to β_t, there is exposure to inflation expectations, exposure to long-term interest rates, and exposure to credit conditions – complex and heterogeneous effects. This combination of different channels makes the estimates highly aggregated. Ultimately, this suggests that the parameter β_t likely has effects that are too diverse and sophisticated across the economy to be generalized as a single factor. Moreover, one cannot rule out the previously discussed possibility that the estimated parameter does not fully represent economic agents' perceptions of Bacen. After all, it is agents' perceptions that alter the intermediate macroeconomic variables through which firms are affected.

In conclusion, the estimates of $\bar{\bar{\lambda}}s\hat{\varepsilon}$ indicate that the only complete specifications are FF3 and FF5. Exposures to size and momentum do not appear to represent sources of systematic risk. The results also indicate the presence of a premium associated with aggressive investment and low profitability in Brazil, with weaker evidence for the investment factor. Exposure to the market factor, in turn, shows indications of the negative premium effect documented by Frazzini and Pedersen (2014). Moreover, it is significant in FF3 and becomes redundant in FF5 with the introduction of additional firm-specific factors. The value factor exhibits an interesting pattern: it is insignificant in FF3 and significant in FF5. This likely stems from the isolation of the value effect promoted by the introduction of the investment and profitability factors – both associated with negative premia for conservative and profitable firms. The estimates of $\bar{\hat{\lambda}}0$ indicate a rejection of the EMH, with ample scope for generating returns above those justified by systematic risks. Finally, the estimate of $\bar{\hat{\lambda}}\hat{\beta}$ does not appear to be statistically significant. While its interpretation is meaningful and theoretically coherent, the excessive aggregation of effects embedded in the theory, combined with localized imprecision in the estimation of β_t, renders it diffuse and insignificant. Moreover, the estimated premium is more likely driven by behavioral biases than by common, non-diversifiable systematic risks.

Table 6: Risk premia results from the Fama-MacBeth regression

$$R_i = \hat{\lambda}_0 + \hat{\lambda}_{\hat{\beta}}\hat{b}_{\hat{\beta},i} + \sum \hat{\lambda}_f \hat{b}_{f,i} + \hat{\lambda}_{s_{\hat{\varepsilon}}} s_{\hat{\varepsilon}} + \hat{\epsilon}_i$$

	Statistic			
Coefficient	Estimated value	Standard Error	t-statistic	p-value
CAPM				
$\bar{\hat{\lambda}}_0$	0.03788	0.00841	4.50561	0.00001
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	0.10177	0.04900	2.07707	0.03882
$\bar{\hat{\lambda}}_{\hat{\beta}}$	0.16961	0.25578	0.66311	0.50788
$\bar{\hat{\lambda}}_{MKT}$	-0.01711	0.00944	-1.81340	0.07098
FF3				
$\bar{\hat{\lambda}}_0$	0.04875	0.00968	5.03416	0.00000
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	0.11624	0.07773	1.49543	0.13640
$\bar{\hat{\lambda}}_{\hat{\beta}}$	-0.06101	0.42869	-0.14231	0.88698
$\bar{\hat{\lambda}}_{MKT}$	-0.03019	0.01243	-2.42790	0.01608
$\bar{\hat{\lambda}}_{SMB}$	0.00440	0.00597	0.73602	0.46260
$\bar{\hat{\lambda}}_{HML}$	0.00561	0.00681	0.82342	0.41126
FF5				
$\bar{\hat{\lambda}}_0$	0.05515	0.01711	3.22302	0.00157
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	0.07107	0.14456	0.49165	0.62372
$\bar{\hat{\lambda}}_{\hat{\beta}}$	1.25231	0.87424	1.43245	0.15420
$\bar{\hat{\lambda}}_{MKT}$	-0.00978	0.02026	-0.48264	0.63009
$\bar{\hat{\lambda}}_{SMB}$	-0.00037	0.01047	-0.03573	0.97155
$\bar{\hat{\lambda}}_{HML}$	0.02879	0.01050	2.74343	0.00686
$\bar{\hat{\lambda}}_{CMA}$	-0.01815	0.01192	-1.52338	0.12987
$\bar{\hat{\lambda}}_{RMW}$	-0.02880	0.01361	-2.11702	0.03599
FF5+Mom				
$\bar{\hat{\lambda}}_0$	0.08508	0.01383	6.15185	0.00000
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	-0.23028	0.12099	-1.90326	0.05983
$\bar{\hat{\lambda}}_{\hat{\beta}}$	0.29373	2.14361	0.13703	0.89128
$\bar{\hat{\lambda}}_{MKT}$	-0.03010	0.03323	-0.90582	0.36716
$\bar{\hat{\lambda}}_{SMB}$	0.00222	0.01893	0.11715	0.90697
$\bar{\hat{\lambda}}_{HML}$	0.01474	0.01824	0.80801	0.42096
$\bar{\hat{\lambda}}_{CMA}$	-0.04538	0.02197	-2.06574	0.04139
$\bar{\hat{\lambda}}_{RMW}$	-0.04349	0.02108	-2.06298	0.04165
$\bar{\hat{\lambda}}_{MOM}$	0.00177	0.03073	0.05747	0.95428

4.3 Validation

In order to validate all estimations, it is necessary to conduct a set of tests on key variables, starting with the residuals of the measurement equation and the state equation of the SSM. Formally, the assumptions regarding these standardized residuals are that they are Gaussian white noise. Therefore, they should be normally distributed, homoskedastic, and free of serial correlation. To assess this, Durbin and Koopman (2012) suggest four diagnostic plots: (1) the time series of the residuals; (2) a histogram with the estimated distribution; (3) a quantile-quantile plot against the normal distribution; and (4) a correlogram. Figure 6 presents the predicted and observed trajectories of the signal – the *ex ante* real interest rate – as well as the trajectory of the residuals. The model appears to fit the observed data well and, at first glance, the residuals do not seem to exhibit clearly abnormal behavior.

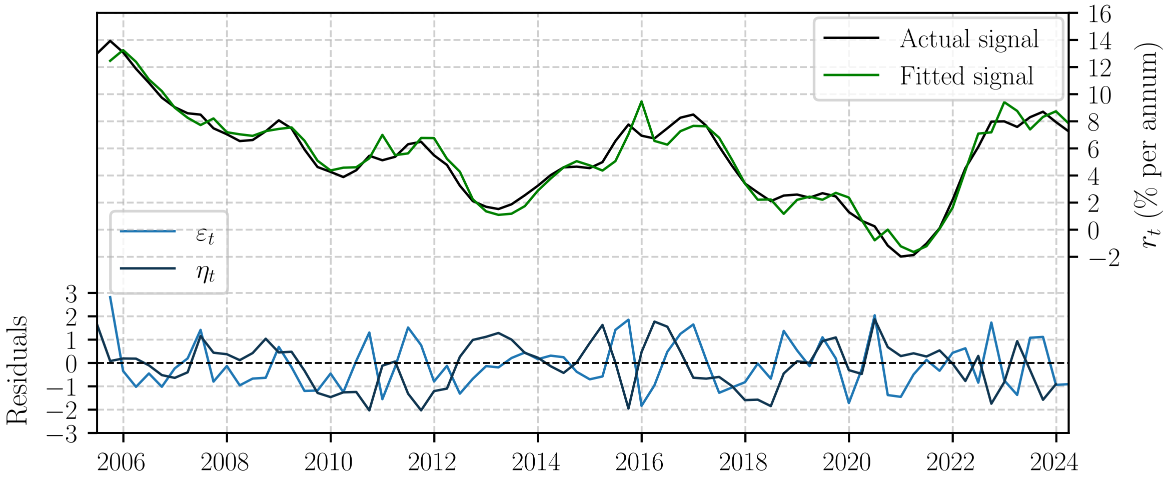
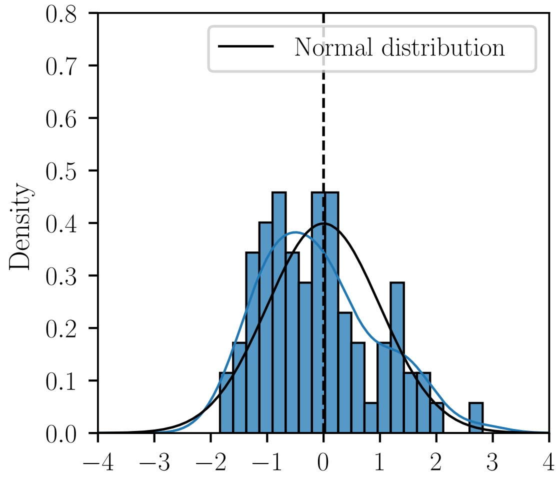
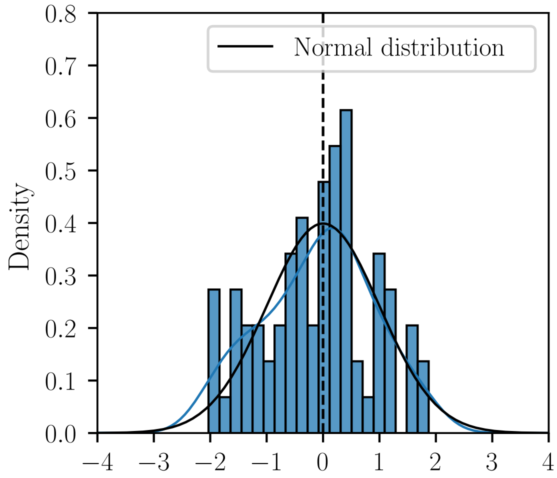


Figure 6: Actual and fitted signal, and residuals from the SSM

Figure 7 presents the histograms of both standardized residuals, along with an estimated density and the normal distribution. They appear to be slightly asymmetric in opposite directions. Figure 8 plots the quantiles of the standardized residuals against the quantiles of the desired normal distribution, represented by the black line. The residuals from the measurement equation seem to adhere less closely to the theoretical quantiles than those from the state equation. Nevertheless, overall, the descriptive evidence indicates that both sets of residuals are relatively close to the normal distribution and do not deviate substantially from it.

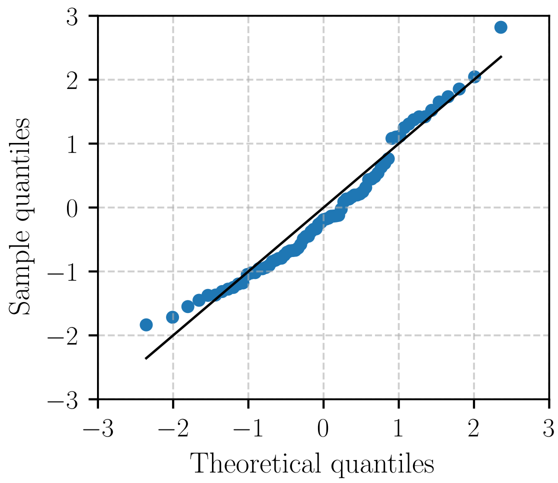


(a) ε_t

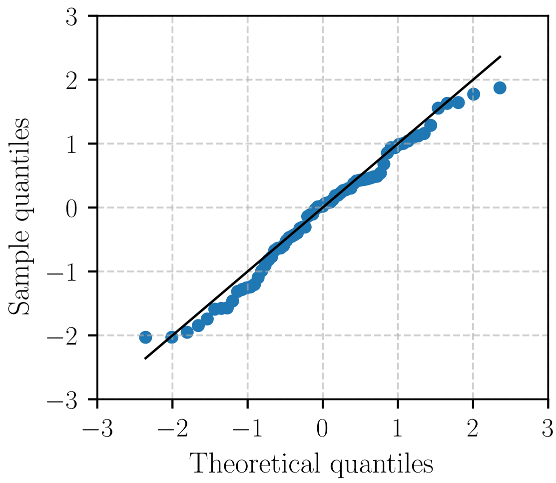


(b) η_t

Figure 7: Histograms and distributions from the SSM standardized residuals



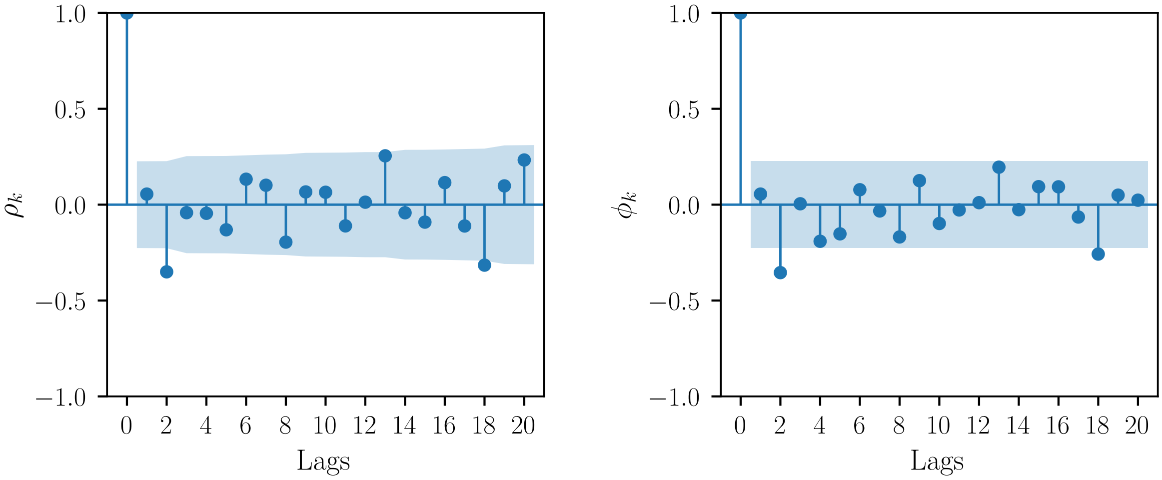
(a) ε_t



(b) η_t

Figure 8: SSM standardized residuals quantiles versus normal quantiles

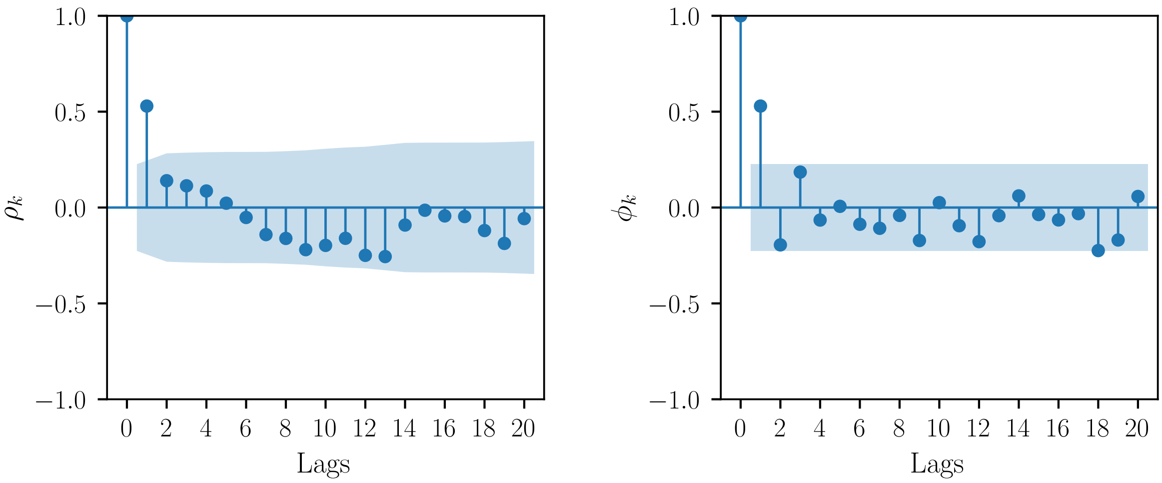
The next assumption, the absence of serial correlation, can be visually assessed using correlograms. Figure 9 presents the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the standardized residuals from the measurement equation. In both cases, most values lie within the confidence interval, with only two lags outside it. Figure 10 presents the same plots for the standardized residuals of the state equation. These exhibit a completely different pattern, with concentration at lag one and decay thereafter. Overall, both sets of standardized residuals appear to display serial correlation due to the values that lie considerably outside the confidence interval at lags one and two.



(a) Autocorrelation function

(b) Partial autocorrelation function

Figure 9: Correlogram of the standardized residuals from the measurement equation



(a) Autocorrelation function

(b) Partial autocorrelation function

Figure 10: Correlogram of the standardized residuals from the state equation

In order to draw precise conclusions regarding these assumptions, a set of formal tests is conducted. Durbin and Koopman (2012) and Harvey (1990) recommend the Jarque-Bera, Ljung-Box, and Goldfeld-Quandt tests to assess, respectively, normality, serial correlation, and heteroskedasticity. These tests originate from the works of Jarque and Bera (1980), Ljung and Box (1978), and Goldfeld and Quandt (1965). Tables 7 and 8 report the results of the three tests for the residuals. As can be observed, the Jarque-Bera test statistic for the residuals of the measurement equation yields a p-value that is statistically significant only at significance levels above 10%. At the conventional 5% level, however, the conclusion is that these residuals are normally distributed. For the residuals of the state equation, the p-value of 46% leads to a failure to reject the null hypothesis of normality at any conventional significance level – full results of the Jarque-Bera test are reported in Appendix A.

Table 7: Tests on the standardized residuals from the measurement equation

Observations	75	t-statistic	p-value
Test:	Jarque-Bera	4.71006	0.09489
	Ljung-Box	19.1675	0.05815
	Goldfeld-Quandt	1.13453	0.36812

Table 8: Tests on the standardized residuals from the state equation

Observations	75	t-statistic	p-value
Test:	Jarque-Bera	1.54643	0.46153
	Ljung-Box	39.25562	0.00005
	Goldfeld-Quandt	0.95767	0.54596

Turning to the Goldfeld-Quandt test for heteroskedasticity, we also observe high p-values, indicating a failure to reject the null hypothesis of homoskedastic residuals. Nevertheless, the Ljung-Box test yields low p-values in both cases, leading to a rejection of the null hypothesis of no serial correlation. For the residuals of the measurement equation, it is possible not to reject the null hypothesis at the 10% significance level; however, the proximity of the p-value to 5% makes rejection more reasonable. The conclusion of these tests is therefore that the residuals are not white noise.

From a statistical perspective, the presence of autocorrelation does not render the parameter estimates biased, but it does make them inefficient, since the residual covariance matrix used by the Kalman filter becomes misspecified. This implies bias in the uncertainty associated with the state, that is, incorrect confidence intervals and impaired inference. In practice, residual autocorrelation is a symptom of part of the series' dynamics being absorbed by the error term. This suggests that the model is misspecified and that systematic patterns are not being captured. Therefore, the presence of serial correlation should not compromise the economic interpretation of β_t, but it may affect the quality of the risk premium estimates, given the increased imprecision in the system.

In the Fama-MacBeth regression stage, there are several issues that must be validated. First, the series β_t cannot contain a unit root; otherwise, the time series regressions would yield unstable coefficients, meaning that the OLS estimator would be biased and inconsistent. Table 9 reports the ADF test with a p-value of 3.56%, indicating rejection of the null hypothesis of a unit root at the 5% significance level. Another relevant assumption of the time series regressions is that the residuals are white noise. As described in the data section, this issue is addressed by excluding stocks whose regressions against the factors produce residuals with serial correlation or heteroskedasticity.

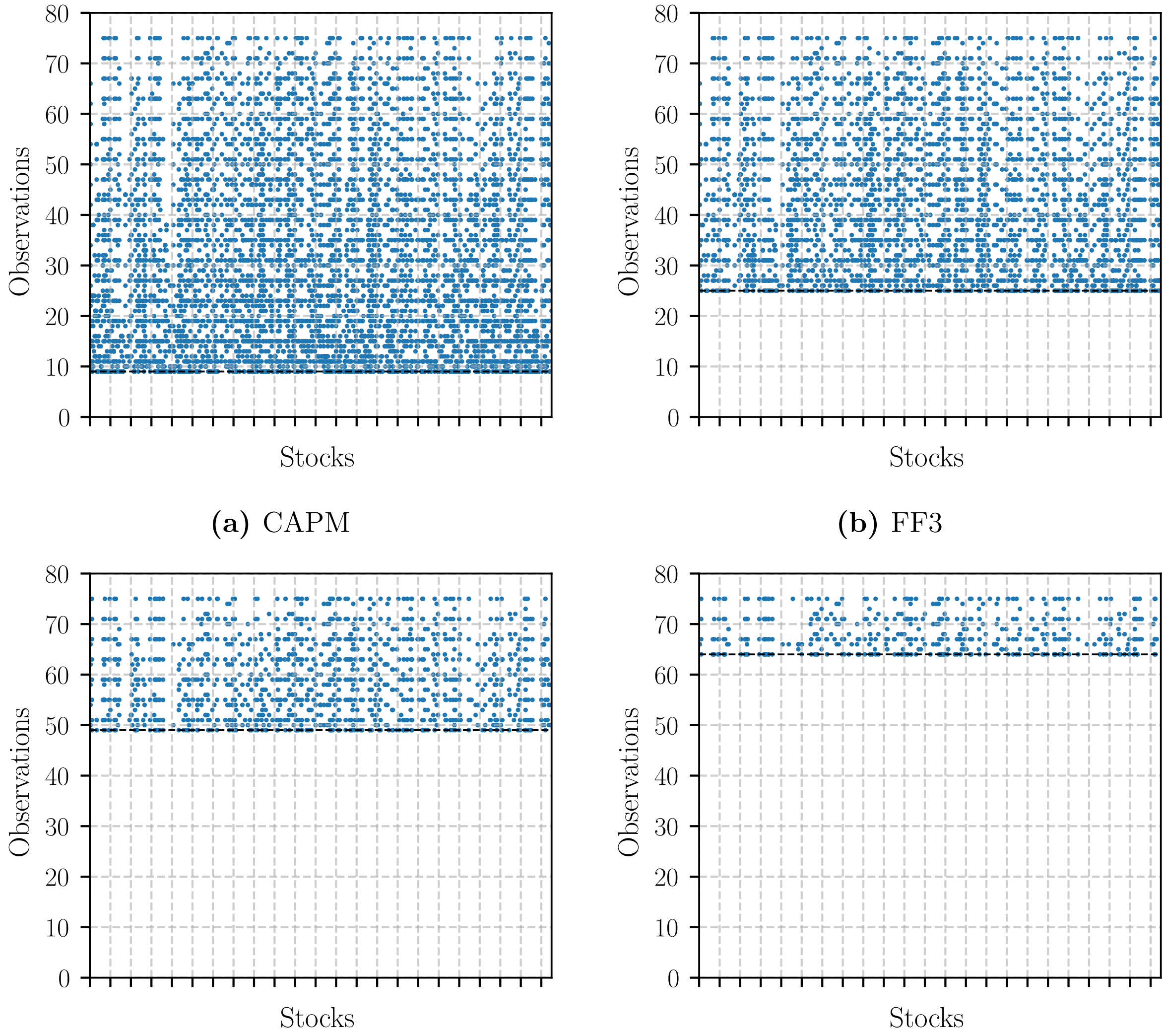
Table 9: ADF test on the Brazilian Central Bank's preferences

Observations	73	t-statistic	p-value
Augmented Dickey-Fuller test statistic		-2.09429	0.03561
Critical test values:	1% level	-2.59748	
	5% level	-1.94539	
	10% level	-1.61384	

Table 10: ADF test equation on the Brazilian Central Bank's preferences

Variable	Estimated value	Standard error	t-statistic	p-value
β_{t-1}	-0.05979	0.02855	-2.09429	0.03996
$\Delta\beta_{t-1}$	0.63741	0.11449	5.56751	0
$\Delta\beta_{t-2}$	-0.36913	0.12957	-2.84894	0.0058
$\Delta\beta_{t-3}$	0.26776	0.11628	2.30276	0.02436

A relevant topic to be discussed concerns the number of observations used in the regressions. As described earlier, stocks' sensitivities to the factors are estimated through individual time series regressions for each asset, updated annually. Therefore, n regressions are estimated for each asset, where n is the number of periods in which the sensitivity value is updated. For each specification – CAPM, FF3, FF5, and FF5+Mom – there are, respectively, 6520, 3568, 1279, and 445 regressions. Note that this number declines because, as more explanatory variables are included, the minimum number of required observations increases, and more stocks are discarded. Consequently, it would be infeasible to report the number of observations for each of these regressions in a conventional manner. In Figure 11, each point represents the number of observations used in each equation estimated for a specific stock at a specific point in time. No point crosses the dotted line, as it represents the minimum number of required observations – determined by the square-of-regressors rule.



(a) CAPM **(b)** FF3 **(c)** FF5 **(d)** FF5+Mom

Figure 11: Observations by time series regression

Although the number of observations is always above the minimum required by the regressions, these values are not particularly large. This occurs due to the use of quarterly data, which limits the number of observations even over a long sample period – 19 years. This issue is especially pronounced for specifications with a larger number of factors, such as in sub-figures 11c and 11d, where the number of observations is very close to the minimum required by the literature. This does not invalidate the estimates, but it represents a limitation, as it reduces precision and increases the variability of the coefficients that are later used as regressors.

Still on the topic of observations, Figure 12 presents the number of observations for each cross sectional regression estimated at each point in time. Once again, we observe that for specifications with more explanatory variables, the number of observations is consistently closer to the minimum, leading to the same limitations discussed above. Moreover, the length of the series shown in Figure 12 corresponds to the number of cross sectional regressions estimated – that is, the number of $\hat{\lambda}$ estimates used to aggregate the risk premium through their mean. For each specification, these values are 67, 51, 27, and 9. It is evident that, in the FF5+Mom specification, the small number of estimates reduces the precision of the risk premium by inflating standard errors.

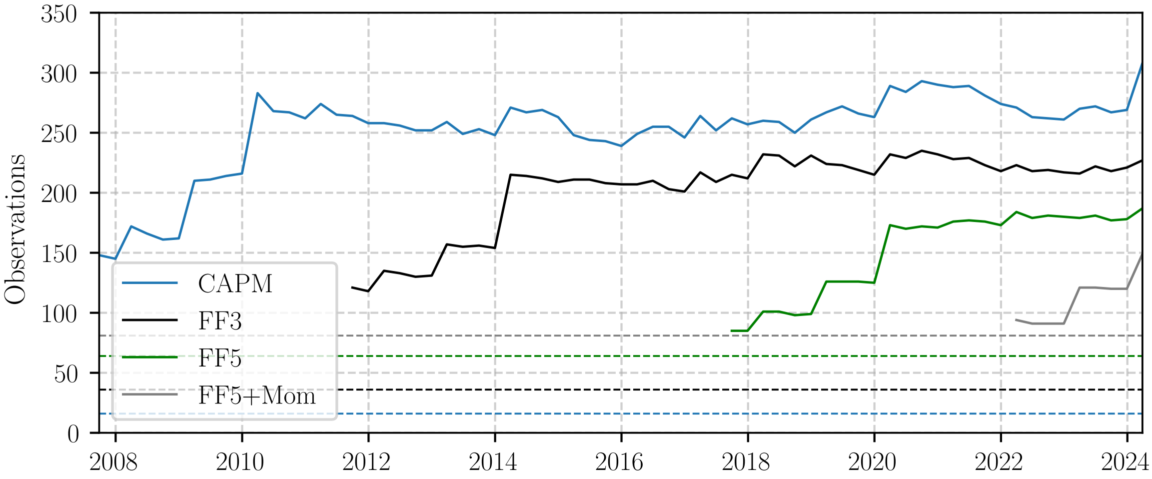


Figure 12: Observations by cross sectional regression

Another important assumption in the time series regressions is that the error term has a zero conditional mean. This assumption follows from the exogeneity of the regressors, according to which the explanatory variables are determined outside the return equation and are not correlated with the error term. In turn, if all sources of systematic risk are included in the regression, the error term can be interpreted as the idiosyncratic return of a stock – that is, the return that does not arise from exposure to systematic risks.

In the context of asset pricing models, factors are constructed from broadly diversified portfolios, which minimizes the impact of stock-specific shocks. The proposed factor β_t does not rely on such a construction mechanism; however, it is a series that represents the preferences of a national-level institution. Therefore, there is no reason to believe that returns arising from shocks specific to each asset are related to β_t or to the other factors, either contemporaneously or serially – implying strong exogeneity. Thus, under the assumption that all relevant sources of systematic risk have been included in the equation – as suggested by the literature and by the interpretation of $\bar{\hat{\lambda}} s\hat{\varepsilon}$, this is the case for FF5 and FF5+Mom – the validation of the assumptions ensures that the OLS estimates of Equation (13) are unbiased and consistent.

For the cross sectional regressions, there is also the assumption of a zero conditional mean of the error term. Again, if all sources of systematic risk are included in the equation, the error term represents the idiosyncratic return at a specific point in time – that is, the return arising from shocks specific to that moment. Since all factor exposures are always estimated using data prior to the cross sectional regression, it is guaranteed that the shock at time t is not incorporated into the estimation of the regressors. Therefore, there is no reason to believe that there is correlation between the error term and the regressors, rendering the OLS estimates of Equation (14) unbiased and consistent.

In conclusion, the validation of the Fama-MacBeth regression assumptions appears to hold only for the more complete FF5 and FF5+Mom models – the latter with a severe limitation in the number of observations. In this sense, the CAPM and FF3 approaches likely yield biased estimates by failing to incorporate relevant sources of systematic risk and, consequently, violating the assumption of a zero conditional mean of the error term. Moreover, the estimates of β_t appear to exhibit some imprecision due to residual serial correlation, which should be kept in mind when interpreting the p-values of the risk premia. Overall, the estimates are validated for the more complete models, albeit with the caveat that the reported p-values are likely underestimated.

4.4 Robustness

In addition, in order to assess the robustness of the results, a monthly version of the econometric model was also estimated. The variables constrained to quarterly frequency were the output gap and the neutral real interest rate, both computed by Bacen. To develop the monthly approach, these series were linearly interpolated. Moreover, following the previous logic of quarterly interest rate smoothing, this monthly Taylor Rule – Equation (18) – introduces three lags of the *ex ante* real interest rate.

$$r_t = (1-\rho_1-\rho_2-\rho_3)\Big(\bar{r}_t + (\beta_t - 1)\big(\mathbb{E}[\pi_t] - \pi_t^T\big) + \gamma\,\tilde{y}_t\Big) + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \rho_3 r_{t-3} + \varepsilon_t \quad (18)$$

Based on this, the same SSM was estimated – full results in Appendix B. Figure 13 shows the similar trajectories from using quarterly or monthly data. This supports the claim that the estimates of Bacen's preferences are robust to different data frequencies.

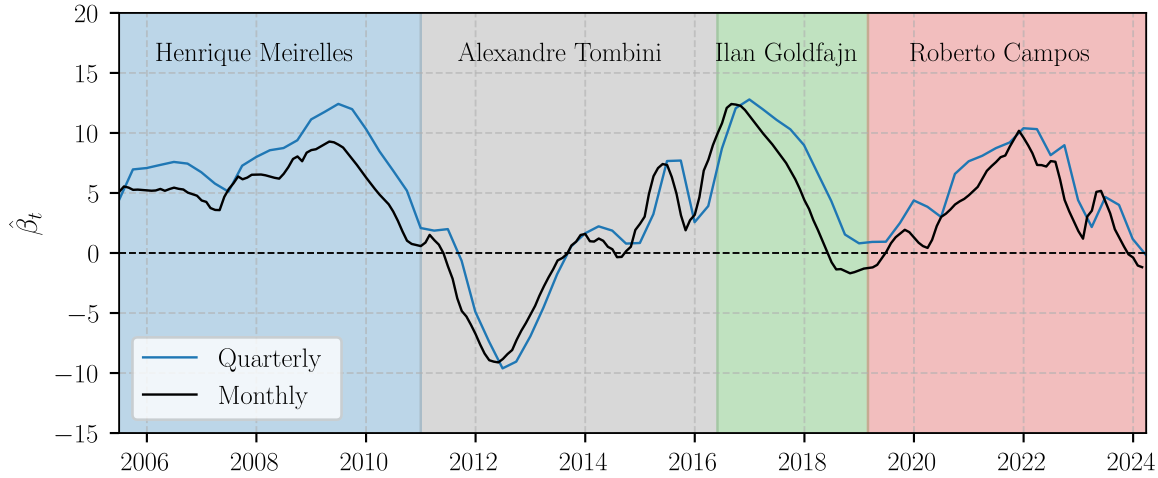
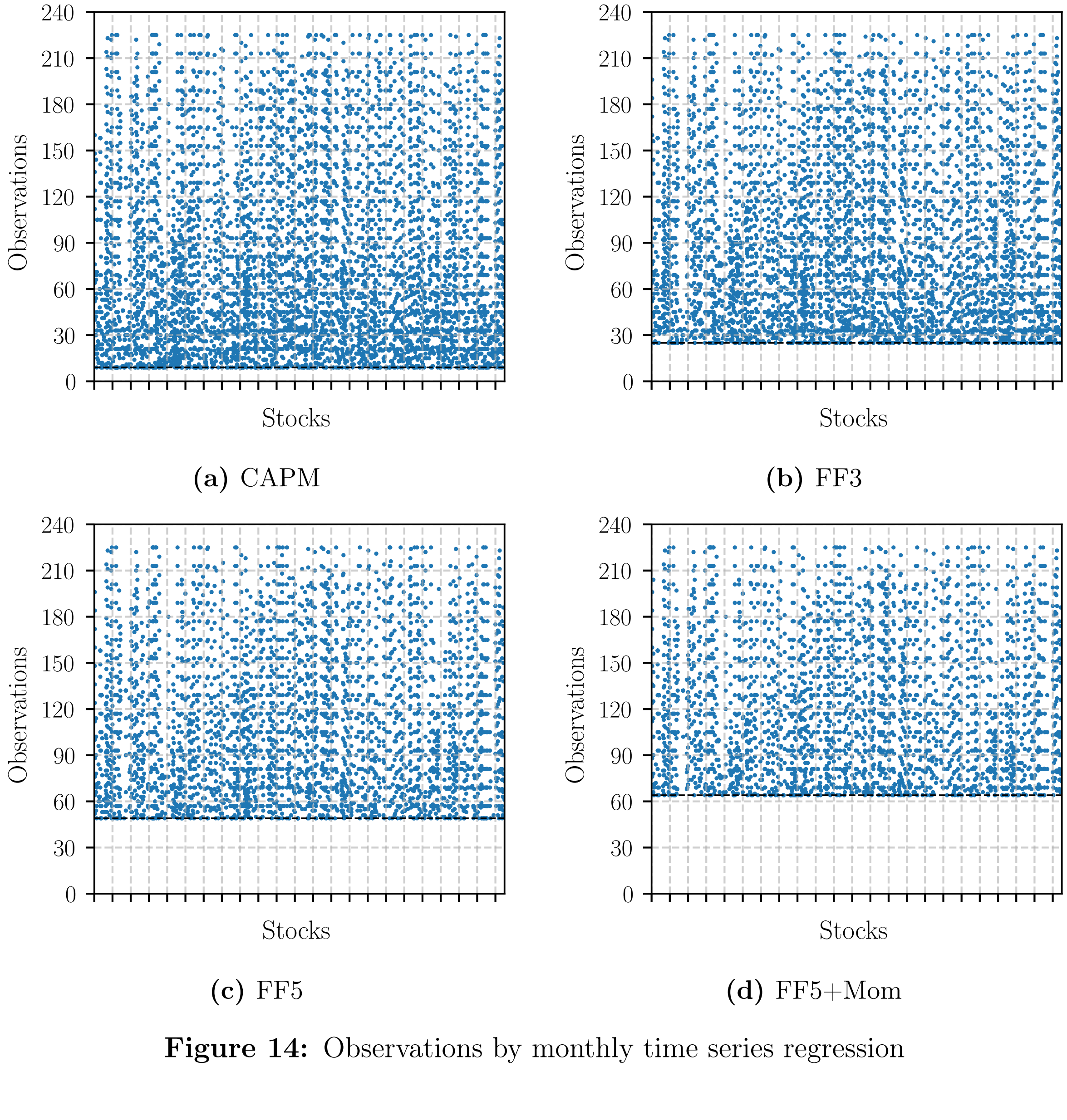


Figure 13: Brazilian Central Bank preferences, monthly and quarterly model



(a) CAPM

(b) FF3

(c) FF5

(d) FF5+Mom

Figure 14: Observations by monthly time series regression

Using this monthly series within the same Fama-MacBeth regression framework yields a much larger amount of data. As shown in Figure 14, for the more complete specifications, the time series regressions that estimate stocks' sensitivities to the factors have a number of observations well above the minimum indicated by the dotted line.

In this sense, the cross sectional regressions also benefited from excluding fewer dates with insufficient data to compute sensitivities – Figure 15. As a result, there is an increase in the number of cross sectional regressions estimated, allowing for a larger sample in the aggregation of the risk premium. Now, for each specification in increasing order of the number of factors, the number of observations used to compute the means is 219, 203, 179, and 159.

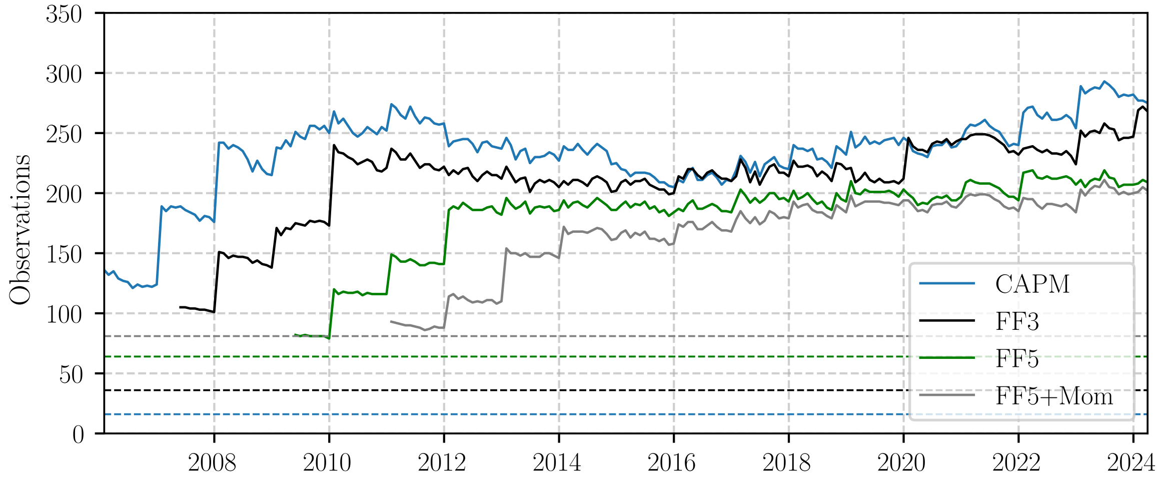


Figure 15: Observations by monthly cross sectional regression

The estimation results are reported in Table 11. First, a generalized reduction in standard errors is observed, which is both positive and expected given that the sample used to compute the means increased across all specifications. The estimates of $\bar{\bar{\lambda}}s\hat{\varepsilon}$ indicate that, unlike the results obtained with quarterly data, FF5+Mom is also a complete specification. Exposure to momentum remains insignificant, while exposure to size appears to be significant only in FF3. The premium associated with low profitability is also present, being statistically significant at the 10% level in FF5 and at the 5% level in FF5+Mom. Investment, in turn, is not statistically significant.

The market factor continues to exhibit a negative premium effect and is highly significant across all specifications. The value factor displays a pattern very similar to that observed with quarterly data: it is insignificant in FF3 and significant in FF5. The estimates of $\bar{\hat{\lambda}}0$ are also consistent, maintaining the same structure. Additionally, all estimates of $\bar{\hat{\lambda}}\hat{\beta}$ have a positive sign, with high p-values in CAPM, FF5, and FF5+Mom. In FF3, the proposed factor exhibits a p-value of 5.3%, indicating the presence of a premium.

The most notable differences arise in the completeness of FF5+Mom, the significance of the size factor in FF3 and of the market factor across all specifications, and the significance of Bacen's preference factor in FF3. However, these are isolated variations that do not materially alter the study's conclusions. Therefore, it is concluded that the estimated risk premia are sufficiently robust to the data frequency.

Table 11: Risk premia results from the monthly Fama-MacBeth regression

$$R_i = \hat{\lambda}_0 + \hat{\lambda}_{\hat{\beta}}\hat{b}_{\hat{\beta},i} + \sum \hat{\lambda}_f \hat{b}_{f,i} + \hat{\lambda}_{s_{\hat{\varepsilon}}} s_{\hat{\varepsilon}} + \hat{\epsilon}_i$$

	Statistic			
Coefficient	Estimated value	Standard error	t-statistic	p-value
CAPM				
$\bar{\hat{\lambda}}_0$	0.01551	0.00305	5.08462	0
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	0.07079	0.02869	2.46718	0.01435
$\bar{\hat{\lambda}}_{\hat{\beta}}$	0.05215	0.14170	0.36801	0.71321
$\bar{\hat{\lambda}}_{MKT}$	-0.01113	0.00272	-4.09140	0.00006
FF3				
$\bar{\hat{\lambda}}_0$	0.01945	0.00283	6.87574	0
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	0.02912	0.03253	0.89535	0.37165
$\bar{\hat{\lambda}}_{\hat{\beta}}$	0.43829	0.22593	1.93996	0.05375
$\bar{\hat{\lambda}}_{MKT}$	-0.01119	0.00319	-3.50992	0.00055
$\bar{\hat{\lambda}}_{SMB}$	0.00364	0.00171	2.13019	0.03434
$\bar{\hat{\lambda}}_{HML}$	0.00189	0.00232	0.81531	0.41584
FF5				
$\bar{\hat{\lambda}}_0$	0.02432	0.00327	7.43412	0
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	0.00221	0.03828	0.05770	0.95406
$\bar{\hat{\lambda}}_{\hat{\beta}}$	0.23251	0.30396	0.76492	0.44535
$\bar{\hat{\lambda}}_{MKT}$	-0.01337	0.00362	-3.69273	0.00030
$\bar{\hat{\lambda}}_{SMB}$	0.00276	0.00238	1.16026	0.24753
$\bar{\hat{\lambda}}_{HML}$	0.00732	0.00292	2.50830	0.01304
$\bar{\hat{\lambda}}_{CMA}$	0.00082	0.00240	0.34332	0.73177
$\bar{\hat{\lambda}}_{RMW}$	-0.00443	0.00265	-1.67010	0.09669
FF5+Mom				
$\bar{\hat{\lambda}}_0$	0.02896	0.00348	8.33074	0
$\bar{\hat{\lambda}}_{s_{\hat{\varepsilon}}}$	-0.04451	0.04211	-1.05710	0.29206
$\bar{\hat{\lambda}}_{\hat{\beta}}$	0.59534	0.37222	1.59946	0.11169
$\bar{\hat{\lambda}}_{MKT}$	-0.01643	0.00411	-3.99839	0.00010
$\bar{\hat{\lambda}}_{SMB}$	0.00359	0.00255	1.40940	0.16066
$\bar{\hat{\lambda}}_{HML}$	0.00758	0.00327	2.32139	0.02153
$\bar{\hat{\lambda}}_{CMA}$	0.00246	0.00270	0.90874	0.36485
$\bar{\hat{\lambda}}_{RMW}$	-0.00676	0.00277	-2.44531	0.01556
$\bar{\hat{\lambda}}_{MOM}$	-0.00125	0.00394	-0.31669	0.75189

5 Conclusion

As described throughout the study, the literature provides a diffuse theoretical foundation connecting a central bank's preferences to asset returns. However, the direct and objective examination of this relationship had not yet been undertaken. In this sense, building on an existing but underexplored foundation, the present study set out to empirically test whether firms' exposure to Bacen's stance represents a source of systematic risk. This work therefore forms part of the ongoing search for new significant factors that characterizes the competitive risk factor literature. In addition, it is also relevant insofar as it evaluates the presence of other factors in the Brazilian market.

The valid and robust FF3 and FF5 estimates indicate a premium associated with firms' positive exposure to Bacen's stance. This arises from the low demand for low-risk and countercyclical stocks – those that benefit during periods when the central bank is more austere and economic activity is more subdued. This interpretation is more consistent with a behavioral bias than with the notion that such exposure constitutes a source of systematic risk. Despite the coherent interpretation, hypothesis tests lead to the conclusion that this premium is only statistically significant at significance levels above 15%. Therefore, using the conventional levels in the literature of 1%, 5%, and 10%, we conclude that this premium does not appear to exist. This result stems from the aggregation of multiple, potentially conflicting effects into a single regressor, which prevents the central bank preference parameter from being a standalone and self-contained factor.

Moreover, the remaining results indicate that the only complete models with sufficient sources of systematic risk are FF3 and FF5. Exposure to the size factor does not appear to represent a source of systematic risk, which is consistent with the findings of Ahn et al. (2015) that the prolonged duration of business cycles weakens the size effect. The market factor only proved relevant in the less complete specifications, with evidence of the effect documented by Frazzini and Pedersen (2014). The results also indicate the presence of premia associated with aggressive investment and low profitability in Brazil, with the former being less pronounced than the latter. Both premia run counter to their original theoretical predictions, with the first already identified and documented by Li and Chen (2022), and the second not yet documented, appearing instead as an anomaly with scope for future investigation. The momentum factor was found to be absent in Brazil, and the estimate of a statistically significant intercept suggests that the Brazilian market is not efficient according to the EMH of Fama (1970), implying that it is possible to earn average returns above those justified by exposure to systematic risks. Finally, the HML factor only became significant with the introduction of the investment and profitability factors, allowing the isolation of value effects. In this way, the present study successfully addresses the proposed research questions, contributing to the asset pricing literature by identifying that the exposure of Brazilian stocks to Bacen's preference parameter does not constitute a source of systematic risk.

Finally, some limitations of this study deserve emphasis. The estimation of Bacen's stance entails a considerable degree of uncertainty, due to serial correlation in the residuals and to the model's imperfection in capturing a parameter that consistently reflects agents' perceptions. In this context, perhaps the most valuable suggestion is the incorporation of the approach proposed by Kim and Nelson (2006) to correct for potential endogeneities in the estimation of time-varying parameters in Taylor Rules. The use of the contemporaneous output gap rather than its expectations is also a limitation. Bacen frequently mentions changes in tax legislation in its Monetary Policy Reports, including measures that are not yet in force. This indicates that part of its response to fiscal policy is prospective. Since the Taylor Rule employed is not forward-looking with respect to the output gap, there is a clear omission of this channel.

In the Fama-MacBeth regression stage, the main limitation is the quarterly frequency of the macroeconomic data and of the time series capturing Bacen's stance. The need to aggregate returns to the quarterly level limits the model's power by yielding a low number of observations. It also results in the loss of a substantial amount of equity data granularity, which is highly relevant for capturing effects. Fortunately, the exercise using monthly data demonstrated reasonable robustness of the estimates. Therefore, the limitations in the State-Space Model stand out as the primary aspect to be improved upon in future research.

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Appendix A: Additional statistics

Table 12: ADF test on the output gap

Observations	75	t-statistic	p-value
Augmented Dickey-Fuller test statistic		-2.51394	0.01249
Critical test values:	1% level	-2.59659	
	5% level	-1.94526	
	10% level	-1.61391	

Table 13: ADF test equation on the deviation of inflation expectations from the target

Variable	Estimated value	Standard error	t-statistic	p-value
$\left(\mathbb{E}[\pi_{t-1}] - \pi^T_{t-1}\right)$	-0.12109	0.04694	-2.57971	0.01212
$\Delta\left(\mathbb{E}[\pi_{t-1}] - \pi^T_{t-1}\right)$	0.47140	0.11388	4.13929	0.00010
$\Delta\left(\mathbb{E}[\pi_{t-2}] - \pi^T_{t-2}\right)$	-0.30935	0.11694	-2.64548	0.01019
$\Delta\left(\mathbb{E}[\pi_{t-3}] - \pi^T_{t-3}\right)$	0.35968	0.11624	3.09429	0.00289
intercept	0.05595	0.08785	0.63691	0.52639
trend	0.00044	0.00202	0.21777	0.82828

Table 14: ADF test on the real *ex ante* interest rate

Observations	75	t-statistic	p-value
Augmented Dickey-Fuller test statistic		-3.87754	0.0035
Critical test values:	1% level	-3.52158	
	5% level	-2.90122	
	10% level	-2.58798	

Table 15: ADF test equation on the real *ex ante* interest rate

Variable	Estimated value	Standard error	t-statistic	p-value
r_{t-1}	-0.08567	0.02209	-3.87754	0.00023
Δr_{t-1}	0.66404	0.08039	8.26056	0
intercept	0.40269	0.13662	2.94744	0.00433

Table 16: Jarque-Bera test on the standardized residuals from the measurement equation

Observations	75	t-statistic	p-value
Jarque-Bera test statistic		4.71006	0.09489
Mean	-0.09262	Skewness	0.619
Median	-0.18901	Kurtosis	2.81131

Table 17: Jarque-Bera test on the standardized residuals from the state equation

Observations	75	t-statistic	p-value
Jarque-Bera test statistic		1.54643	0.46153
Mean	-0.08791	Skewness	-0.14409
Median	0.01935	Kurtosis	2.35571

Appendix B: Monthly model

Table 18: Monthly State-Space Model estimates

Coefficient	Estimated value	Standard error	z-statistic	p-value
$\hat{\sigma}_\varepsilon$	0.48637	0.02547	19.09826	0
$\hat{\sigma}_\eta$	1.94119	0.58510	3.31770	0.00091
$\hat{\rho}_1$	0.48108	0.07246	6.63909	0
$\hat{\rho}_2$	0.40279	0.06052	6.65594	0
$\hat{\rho}_3$	0.05093	0.06569	0.77523	0.43820
$\hat{\gamma}$	1.82030	0.65546	2.77708	0.00548
	Final state	Root MSE	z-statistic	p-value
$\hat{\beta}$	-1.18114	4.70013	-0.25130	0.80158
Observations	228	Akaike Information Criterion		1.69254
Log-likelihood	-184.41026	Schwarz Information Criterion		1.78363
Parameters	6	Hannan-Quinn Information Criterion		1.72930

Table 19: Tests on the monthly standardized residuals from the measurement equation

Observations	225	t-statistic	p-value
Test:	Jarque-Bera	0.7952	0.67193
	Ljung-Box	51.69256	0.00001
	Goldfeld-Quandt	0.64942	0.97845

Table 20: Tests on the monthly standardized residuals from the state equation

Observations	225	t-statistic	p-value
Test:	Jarque-Bera	6.4677	0.03941
	Ljung-Box	352.13163	0
	Goldfeld-Quandt	1.42273	0.04905

Table 21: ADF test on the Brazilian Central Bank's monthly preferences

Observations	227	t-statistic	p-value
Augmented Dickey-Fuller test statistic		-2.36578	0.01771
Critical test values:	1% level	-2.57523	
	5% level	-1.94224	
	10% level	-1.61576	

Table 22: ADF test equation on the Brazilian Central Bank's monthly preferences

Variable	Estimated value	Standard error	t-statistic	p-value
β_{t-1}	-0.01205	0.00509	-2.36578	0.01885
$\Delta\beta_{t-1}$	0.74770	0.04416	16.93269	0

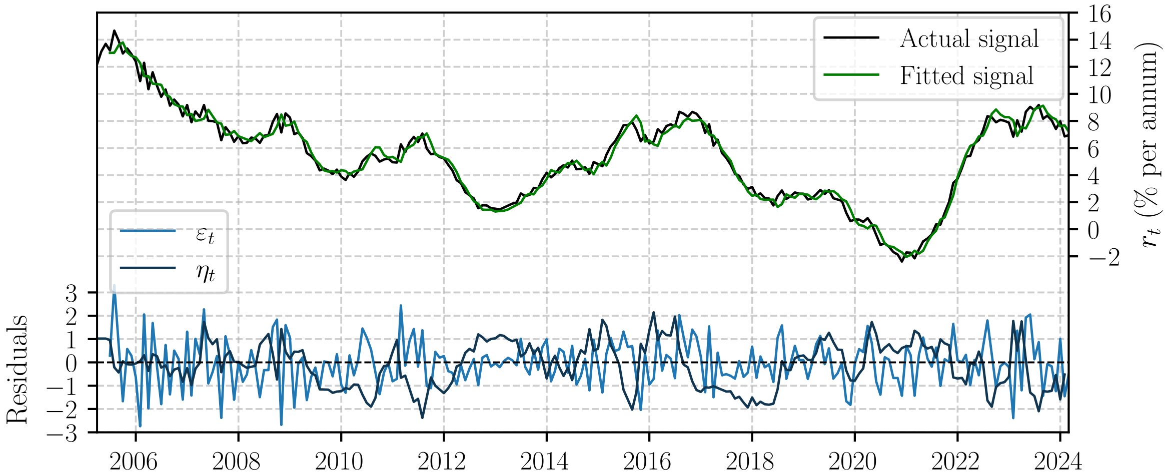

Figure 16: Actual and fitted signal, and residuals from the monthly SSM