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Essays in Empirical Finance: An Analysis of Brazilian Hedge Funds

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor : Prof. Nathalie Christine Gimenes
Co-advisor: Prof. Marcelo Cunha Medeiros

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To my wife and son.

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Abstract

Vogt, Pedro; Gimenes, Nathalie Christine (Advisor); Medeiros, Marcelo Cunha (Co-Advisor). **Essays in Empirical Finance: An Analysis of Brazilian Hedge Funds**. Rio de Janeiro, 2025. 97p. Tese de doutorado – Departamento de Economia, Pontifíciacia Universidade Católica do Rio de Janeiro.

This dissertation consists of three essays on dynamic trading by Brazilian macro hedge funds. In the first essay, we investigate whether aggregate hedge fund time-varying risk exposures to a set of risk factors contain predictive information about future inflation. We estimate time-varying exposures using state-space models and structural break models applied to daily Brazilian macro hedge fund returns. We find that macro hedge fund exposure to the exchange rate has explanatory power over cumulative 12-month ahead inflation. We also find that incorporating exchange rate exposure data into high-dimensional inflation forecasting models yields meaningful performance improvements. In the second essay, we investigate hedge fund replication strategies that condition on cross-sectional dispersion in estimated macro hedge fund exposures. Simple replication strategies yield modest and insignificant performance, but conditioning positions on a measure of dispersion substantially improves risk-adjusted returns. Dispersion-conditional strategies achieve improved Sharpe ratios and lower maximum drawdowns, suggesting that cross-sectional agreement is a strong signal for market timing. In the third essay, we explore the cross-section of Brazilian hedge fund returns using a novel measure of risk factor timing intensity - the tracking error between returns implied by estimated time-varying versus assumed-constant factor exposures. Fama-MacBeth regressions reveal that timing intensity significantly predicts monthly excess returns, robust to controlling for fund characteristics and exposure to conventional risk factors. This finding extends the active share literature to hedge funds and provide actionable insights for fund selection.

Keywords

Hedge Funds Risk Exposure Inflation Forecasting Machine Learning

Resumo

Vogt, Pedro; Gimenes, Nathalie Christine; Medeiros, Marcelo Cunha. **Ensaios em Finanças Empíricas: Uma Análise de Hedge Funds Brasileiros**. Rio de Janeiro, 2025. 97p. Tese de Doutorado – Departamento de Economia, Pontifíciacia Universidade Católica do Rio de Janeiro.

Esta tese é composta por três ensaios sobre o posicionamento dinâmico de macro hedge funds brasileiros. No primeiro ensaio, investigamos se as exposições agregadas variantes no tempo de hedge funds a um conjunto de fatores de risco contêm informação preditiva sobre inflação futura. Estimamos exposições variantes no tempo usando modelos de espaço de estados e modelos de quebra estrutural aplicados a retornos diários de hedge funds macro brasileiros. Encontramos que a exposição de hedge funds macro à taxa de câmbio tem poder explicativo sobre a inflação future acumulada em 12 meses. Também encontramos que a incorporação de dados de exposição à taxa de câmbio em modelos de alta dimensionalidade para previsão de inflação gera melhorias relevantes. No segundo ensaio, investigamos estratégias de replicação de hedge funds que condicionam na dispersão na cross-section das exposições estimadas de hedge funds macro. Estratégias simples de replicação geram desempenho modesto e não significativo, mas condicionar posições em uma medida de dispersão melhora substancialmente os retornos ajustados ao risco. Estratégias condicionais à dispersão alcançam índices de Sharpe maiores e drawdowns máximos menores, sugerindo que concordância cross-sectional é um forte sinal para timing de mercado. No terceiro ensaio, exploramos a cross-section dos retornos de hedge funds brasileiros usando uma medida nova de intensidade de timing de fatores de risco - o tracking error entre retornos implícitos por exposições estimadas variantes no tempo versus exposições assumidas constantes. Regressões Fama-MacBeth revelam que a intensidade de timing prevê significativamente retornos excedentes mensais, mesmo após controlar por características dos fundos e suas exposição a fatores de risco convencionais. Esse resultado estende a literatura de active share para hedge funds e fornece insights práticos para seleção de fundos.

Palavras-chave

Hedge Funds Exposição a Risco Previsão de inflação Aprendizado de Máquina

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Gold and atium are complements, like the other metal pairs. Atium lets you see, marginally, into the future. Gold works in a similar way, but it lets you see into the past.

Brandon Sanderson, *Mistborn: The Final Empire.*

Introduction

For decades, hedge funds have been drawing the attention of investors, regulators and researchers. Hedge funds are a sophisticated and often opaque class of market participants that are active in many markets. By employing dynamic and complex trading strategies hedge funds may play a role in facilitating the well-functioning of markets, while also potentially being a source of systemic risk by playing a role in the propagation of financial stress (Gregoriou & Duffy, 2006). Multiple studies document that (at least some) hedge funds exhibit timing ability across various markets and strategies, including market conditions (Capocci *et al.*, 2005; Stafylas *et al.*, 2018), liquidity (Cao *et al.*, 2013), and macroeconomic uncertainty (Bali *et al.*, 2014). Yet, much remains unknown about if and how hedge funds positioning data may be used as forward-looking indicators of future economic and market conditions.

This dissertation investigates Brazilian macro hedge funds, leveraging unique daily Brazilian data that eliminate survivorship and backfill biases endemic to most hedge fund databases (Almeida *et al.*, 2021). The Brazilian regulatory environment mandates daily disclosure of fund returns, enabling more precise estimation of time-varying risk exposures and providing a clean view of hedge fund behavior. Brazilian macro hedge fund industry manage substantial assets and trade heavily in liquid instruments related to equities, interest rates and currencies. This combination of data quality, market liquidity, and meaningful macroeconomic variation creates an ideal laboratory for examining fundamental questions about the informational value of real-time hedge fund positioning.

The dissertation comprises three self-contained but interconnected essays, each addressing a distinct research question with practical implications for different stakeholders. Chapter 1 investigates whether macro hedge fund risk exposures predict future inflation. We estimate time-varying exposures using state-space models and structural break models. We find that aggregate hedge fund positioning in the BRL/USD exchange rate significantly forecasts inflation realizations. These findings suggest that policymakers and forecasters can achieve meaningful improvements by monitoring hedge fund exposures as real-time indicators.

Chapter 2 examines whether hedge fund replication strategies can be enhanced by conditioning on cross-sectional dispersion in estimated exposures. A simple replication strategy that mimics aggregate hedge fund positioning yields modest performance, but conditioning positions on a measure of dispersion across hedge funds substantially improves results. Dispersion-conditional strategies achieve improved risk-adjusted returns with substantially lower maximum drawdowns. These results are relevant for market participants interested in capturing hedge fund returns through systematic replication strategies, suggesting that cross-sectional agreement in positioning may signal higher conviction in the future direction of asset returns.

Chapter 3 investigates whether fund-level risk factor timing intensity, measured as the tracking error between returns implied by time-varying versus assumed-constant estimated factor exposures, predicts cross-sectional returns. Fama-MacBeth regressions reveal that this measure significantly predicts monthly excess returns, robust to controlling for fund characteristics, factor loadings, and fees. These findings extend the active share literature to hedge funds and provides actionable insight for investors engaged in fund selection.

The following chapters develop these themes in detail, presenting empirical evidence on how macro hedge fund positioning informs inflation forecasts, enhances replication strategies, and predicts fund-level performance.

1
What do Hedge Funds Know About Inflation? Incorporating Hedge Fund Risk Exposure Data into Inflation Forecasts

Abstract. This essay investigates whether macro hedge fund risk exposures contain predictive information about future inflation. Using daily data on 438 Brazilian macro hedge funds from January 2006 to August 2024, we estimate time-varying exposures to seven macro-sensitive risk factors using Kalman filter and optimal changepoint regression methods. The central finding is that hedge fund exposure to the BRL/USD exchange rate significantly predicts cumulative 12-month inflation, even after controlling for professional survey forecasts. In a pseudo out-of-sample exercise, we find that incorporating hedge fund exposure to the exchange rate data into low and high-dimensional forecasting models yields statistically significant improvements. A simple linear model that incorporates exchange rate exposure as an inflation predictor achieves the lowest mean absolute error (MAE) for cumulative 12-month ahead inflation across several models, reducing MAE by 3% relative to the benchmark FOCUS forecast. The results strongly suggest that hedge fund positioning provides forward-looking information about macroeconomic conditions beyond traditional predictors.

Keywords: inflation forecasting; hedge funds; risk exposures; machine learning; factor models

1.1 Introduction

Hedge funds are a sophisticated class of investors that often employ dynamic and complex trading strategies, frequently adjusting positions in response to shifts in economic conditions and underlying fundamentals (Patton & Ramadorai, 2013). Multiple studies document that hedge funds, at least in part, appear to exhibit macro timing ability, successfully reducing systematic risk exposure prior to adverse economic periods (Capocci *et al.*, 2005; Bali *et al.*, 2014; Stafylas *et al.*, 2018; Stafylas & Andrikopoulos, 2020). Macro hedge funds, in particular, trade assets whose returns are highly correlated with macroeconomic variables, including equities, currencies, and different tenors of interest rate curves.

Building upon this existing literature, we investigate the following hypothesis: hedge fund positioning may contain exploitable forward-looking information about macroeconomic conditions. If hedge fund positioning is indicative of macro-timing ability with respect to risk factors that co-move with macroeconomic surprises, their risk factor loadings could contain predictive information about future macroeconomic conditions. To the best of our knowledge, this conjecture has not been tested explicitly in the forecasting literature. We aim to close this gap at the intersection of macro forecasting and hedge fund research.

We investigate this hypothesis applied to Brazilian inflation. Understanding and forecasting inflation remains a central challenge in macroeconomics and a critical concern for policymakers, investors, and market participants. Moreover, Brazilian inflation has exhibited substantial variation over time, including episodes of elevated inflation and uncertainty that provide meaningful cross-sectional variation for testing predictive relationships. Additionally, Brazil has daily reporting requirements for all funds, allowing for more precise estimation of hedge fund time-varying risk exposures and mitigating survivorship and backfill biases that plague much hedge fund research.

This essay formally tests whether incorporating macro hedge fund risk exposure (HFRE) data into several forecasting models can improve inflation forecasts relative to professional survey expectations and benchmark models. Using daily returns on 438 Brazilian macro hedge funds spanning January 2006 to August 2024, we employ two complementary methods to estimate time-varying exposures to seven risk factors: (1) a state-space model with autoregressive latent variables estimated via a Kalman filter procedure, allowing for smooth beta evolution, and (2) a structural break model estimated via optimal changepoint regression that identifies discrete structural shifts in

exposures. Both methods capture how hedge funds dynamically adjust their positioning in Brazilian equities, Brazilian bonds (1-year and 5-year maturities), inflation-linked bonds, the BRL/USD exchange rate, US equities, and US bonds.

The estimated risk exposures are then incorporated as predictors into several forecasting frameworks, including ordinary least squares (OLS), adaptive LASSO, and random forests. These models are evaluated in a pseudo out-of-sample exercise from August 2016 to August 2024, comparing forecasts at horizons ranging from 1 to 12 months ahead against the benchmark FOCUS forecasts - the median forecast produced by a set of major financial institutions and surveyed weekly by the Brazilian Central Bank.

Main Results. Three key findings emerge from the analysis. First, a direct regression of realized cumulative inflation on FOCUS forecasts and hedge fund risk exposures reveals that macro hedge fund aggregate exposure to the BRL/USD exchange rate (USDRE) significantly predicts 12-month cumulative inflation, even after controlling for FOCUS forecasts. Specifically, the coefficient on USDRE is 0.21 with a Newey-West adjusted t-statistic of 2.05, suggesting a relationship that is statistically significant and economically meaningful. Notably, the coefficient associated with the FOCUS forecast loses statistical significance at this horizon. Other macro hedge fund estimated exposures (Brazilian equities, domestic bonds, and inflation-linked securities) do not exhibit statistically significant predictive power at conventional significance levels.

Second, incorporating USDRE into out-of-sample forecasting models yields economically and statistically meaningful improvements. Forecasts from a simple linear model incorporating USDRE as an additional predictor often performed statistically better - in one-tailed Diebold-Mariano tests with conventional confidence levels - than the simple FOCUS forecast. Furthermore, high-dimensional models augmenting a large set of predictors with USDRE consistently outperformed their non-USDRE counterparts for several horizons. For the 12-month cumulative horizon, USDRE-augmented adaptive LASSO and random forest forecasts achieved better performance, in terms of lower root mean squared error (RMSE), than their non-USDRE direct benchmark. In the case of adaptive LASSO forecasts, the USDRE-variant was found to statistically beat the FOCUS forecasts while the non-USDRE counterpart did not achieve any level of statistical significance.

Third, we also find that the predictive performance of both low and high-dimensional models relative to the FOCUS forecast may be highly state-

dependent and concentrated in periods of elevated inflation uncertainty. When conditioning on months where the FOCUS forecasts exhibits high disagreement (standard deviation of long-term inflation projections above the sample median), cumulative 6-month and 12-month forecasts from all models achieve lower RMSE relative to FOCUS forecasts. During low-uncertainty periods, in contrast, the gains from all forecasting models are more modest and often statistically insignificant, although there are still improvements from incorporating USDRE.

Contribution. This essay makes three contributions to the literature. First, it introduces hedge fund risk exposure data as a novel predictor in inflation forecasting. While recent studies have expanded the set of variables considered for macroeconomic forecasting, including commodity futures open interest (Hong & Yogo, 2012), global liquidity measures (D'Agostino & Surico, 2009), and text-based economic narratives (Hong *et al.*, 2024), hedge fund positioning has not previously been exploited as an inflation predictor. This represents an important extension, as hedge funds aggregate diverse information sources and express forward-looking views through their portfolio allocations.

Second, this essay contributes to the literature on forecasting Brazilian inflation with high-dimensional models. Studies such as Garcia *et al.* (2017) and Medeiros *et al.* (2021) have demonstrated that penalized regression methods (LASSO, ridge) and machine learning techniques (random forests, boosting) perform well relative to traditional benchmarks. Our analysis extends these findings by showing that such models exhibit superior performance specifically during periods of elevated inflation uncertainty. This result has practical implications: high-dimensional models may not be uniformly better than survey forecasts, but rather provide disproportionate value precisely when forecasting is most difficult and consensus views may be least reliable. This state-dependence has received limited attention in prior Brazilian inflation forecasting research.

Third, this work provides empirical evidence that hedge fund positioning contains forward-looking information about macroeconomic variables, supporting theories of hedge fund market-timing ability. Related research connects hedge fund returns to macroeconomic risks (Bali *et al.*, 2014) and documents that funds reduce risk exposure before adverse periods (Stafylas & Andrikopoulos, 2020), but direct tests of whether hedge fund positioning predicts macroeconomic outcomes remain scarce. Our findings suggest that policymakers and forecasters may benefit from monitoring hedge fund exposures as a real-time signal, complementing traditional indicators.

The remainder of this essay proceeds as follows. Section 1.2 reviews relevant literature on inflation forecasting, hedge fund behavior across business cycles, and methods for estimating time-varying risk exposures. Section 1.3 describes the data, including the macro hedge fund sample and risk factors. Section 1.4 presents the methodology for estimating hedge fund risk exposures according to complementary models, as well as forecasting framework and evaluation metrics. Section 1.5 reports the main results. Section 1.6 concludes with a discussion of implications and potential extensions. Appendices 1.A provides main results using hedge fund risk exposure estimated assuming a state-space model with autoregressive latent betas and estimated rhtough a Kalman filter procedure. Appendices 1.B provided details on the adaptive LASSO and random forest procedures used and also provides the set of regressors used when computing forecasts in high-dimension.

1.2 Literature Review

This essay draws on three interconnected strands of literature: inflation forecasting methods and predictors, hedge fund behavior across the business cycle, and estimation of time-varying risk exposures.

Inflation Forecasting. The inflation forecasting literature is vast, with researchers proposing diverse sets of predictors and methodologies. Early work emphasized Phillips curve relationships, with Stock & Watson (1999) finding that models incorporating aggregate activity indicators outperform other macroeconomic variables for US inflation, though Atkeson & Ohanian (2001) reach more pessimistic conclusions about Phillips curve predictability. Asset prices have also received substantial attention: Stock & Watson (2003) demonstrate that combining forecasts based on interest rates, term spreads, stock returns, and exchange rates improves upon univariate benchmarks. For commodity-exporting economies, Chen *et al.* (2010) show that world commodity price aggregates exhibit predictive power for inflation.

Survey-based forecasts represent an important benchmark. Multiple studies document that professional forecaster surveys often outperform model-based forecasts (Ang *et al.*, 2007; Faust & Wright, 2013), though there is heterogeneity in forecaster quality D'Agostino *et al.* (2012). Some evidence suggests US inflation has become harder to predict over time (Stock & Watson, 2007), motivating the search for alternative predictors and methods.

The development of high-dimensional modeling techniques has opened new avenues for incorporating rich information sets into inflation forecasts.

Stock & Watson (2002) find that diffusion indexes constructed via principal component analysis perform well for US macroeconomic series. Forni *et al.* (2003) employ a dataset of 447 macroeconomic variables and demonstrate that financial variables improve Euro area inflation forecasts. In the Brazilian context, Garcia *et al.* (2017) show that penalized regression methods - including LASSO, adaptive LASSO, and complete subset regressions - perform well in real-time inflation forecasting when applied to a broad set of predictors encompassing professional forecasts, prices, economic activity, interest rates, labor markets, and financial indicators. Medeiros *et al.* (2021) extend this work by demonstrating that nonlinear machine learning methods such as random forests and boosting provide additional gains. Several other studies confirm the value of high-dimensional approaches for Brazilian inflation (Medeiros *et al.*, 2016; Araujo & Gaglianone, 2023).

This essay contributes to this literature by incorporating hedge fund risk exposure data - a financial market-based signal reflecting informed investors' positioning - into high-dimensional forecasting frameworks and documenting when such data provides incremental predictive power.

Hedge Fund Activity Across the Business Cycle. Patton & Ramadorai (2013) document that hedge funds frequently adjust positions in response to shifting economic conditions. Evidence suggests that hedge fund returns exhibit exposure to systematic risk factors: Asness *et al.* (2001) find significant equity market exposure across hedge fund strategies, while Fung & Hsieh (1997, 2001) demonstrate that trend-following strategies comprise a substantial component of hedge fund returns.

Several studies document that hedge funds successfully reduce systematic risk exposure before adverse economic periods (Stafylas *et al.*, 2018; Capocci *et al.*, 2005; Stafylas & Andrikopoulos, 2020), consistent with market timing ability. Some work also links hedge fund returns to tail risk and extreme events (Agarwal & Naik, 2004; Almeida *et al.*, 2021). More directly related to this essay, Bali *et al.* (2014) show that hedge funds more exposed to macroeconomic uncertainty earn higher risk-adjusted returns, suggesting hedge funds actively manage macro risk exposures.

Despite this evidence of hedge fund responsiveness to macroeconomic conditions, prior research has not directly tested whether hedge fund positioning predicts future macroeconomic realizations. This essay fills that gap by examining whether time-varying hedge fund exposures forecast inflation.

Estimation of Time-Varying Risk Exposures. Accurately measuring time-varying hedge fund risk exposures is a broad topic of research. The liter-

ature has developed several approaches to estimate dynamic factor loadings. Rolling window regressions offer a simple and transparent approach to capture local dynamics in betas, though they impose arbitrary window lengths and treat parameters as static within each window. This method has been extensively used to assess hedge fund exposures to market and style factors (Hasanhodzic & Lo, 2007; Duanmu *et al.*, 2020; O'Doherty *et al.*, 2017).

State-space models estimated via the Kalman filter provide a more flexible framework, allowing latent betas to evolve stochastically over time. These models are widely employed in the hedge fund literature to capture smooth and continuous exposure adjustments (Bollen & Whaley, 2009; Racicot & Théoret, 2016; Mamaysky *et al.*, 2008; Amisano & Savona, 2017; Lambert & Platania, 2020). In these settings, betas are modeled as latent autoregressive processes, and the Kalman filter delivers time-varying estimates that can be interpreted as the manager's dynamic positioning across macro and financial factors.

An alternative strand of research employs structural break models estimated through optimal changepoint regressions, which identify discrete shifts in factor loadings rather than continuous adjustments. These approaches are particularly suitable when funds rebalance portfolios abruptly or when macroeconomic regimes change sharply. Studies such as Bollen & Whaley (2009) and Siegmann & Stefanova (2017) use breakpoint methods to detect significant shifts in hedge fund betas and liquidity relationships, while Andrews *et al.* (1996) provide the econometric foundation for optimal changepoint testing.

1.3 Data

1.3.1 Macro Hedge Funds

Our sample of funds is comprised of Brazilian investment funds live between Januar 2006 and August 2024 and that meet the following criteria: (i) are actively managed (excludes index funds and funds-of-funds), (ii) have at least 48 months of return history during the sample period, (iii) are classified as "multimercado" (multi-strategy funds, which implies they are not equity focused), (iv) have its investment style classified as "Multimercado Macro" (multi-strategy fund with macro focus), "Multimercado Livre" (multi-strategy fund with no mandate restriction) or has no defined investment style, and, (v) has no identified mandate restriction (leverage, short-selling) and charges performance fees of at least 10% - consistent with the fee and incentive

structure that characterize hedge funds globally.

After applying these criteria, the sample includes 438 unique funds spanning the sample period. Brazilian regulation requires daily reporting of fund returns of all liquid funds, mitigating survivorship bias and backfill issues that plague international hedge fund databases. Importantly, the regulatory mandate requires funds to report returns within 2 business days. In our estimation procedures, we restrict the use of fund return data to information available at least 5 business days prior, making our approach conservative and ensuring that estimated hedge fund exposures could be observed in real time by market participants. Table 1.1 reports the evolution of the sample over time.

Table 1.1: Descriptive statistics of the macro hedge fund sample

Year	Funds	Median NAV (mm)	Median age (yrs)	Median mgmt fee (%)	Median pfee (%)	Total AUM (bn)	Av. return (%)
2006	90	79.02	4.20	2.00	20	58.10	1.76
2007	121	105.91	4.13	2.00	20	98.04	2.68
2008	151	41.26	3.44	2.00	20	64.76	-3.74
2009	173	64.27	3.73	2.00	20	100.19	10.89
2010	196	53.16	3.72	2.00	20	115.65	2.17
2011	219	49.43	4.19	2.00	20	115.89	1.08
2012	221	64.93	4.55	2.00	20	153.79	6.90
2013	220	70.99	5.03	2.00	20	153.33	2.89
2014	224	54.81	5.54	2.00	20	128.63	-1.06
2015	225	60.86	6.05	2.00	20	108.88	5.89
2016	223	67.88	6.65	2.00	20	114.69	4.15
2017	222	109.47	6.75	2.00	20	181.98	5.59
2018	234	132.83	6.30	1.98	20	225.30	2.79
2019	254	139.76	5.80	1.98	20	283.97	7.44
2020	282	105.81	5.22	2.00	20	310.25	11.37
2021	263	102.49	5.98	2.00	20	257.36	0.86
2022	249	121.40	6.67	2.00	20	249.40	6.16
2023	238	98.36	7.67	2.00	20	196.91	-1.19
2024	228	87.67	8.50	2.00	20	143.31	-2.23

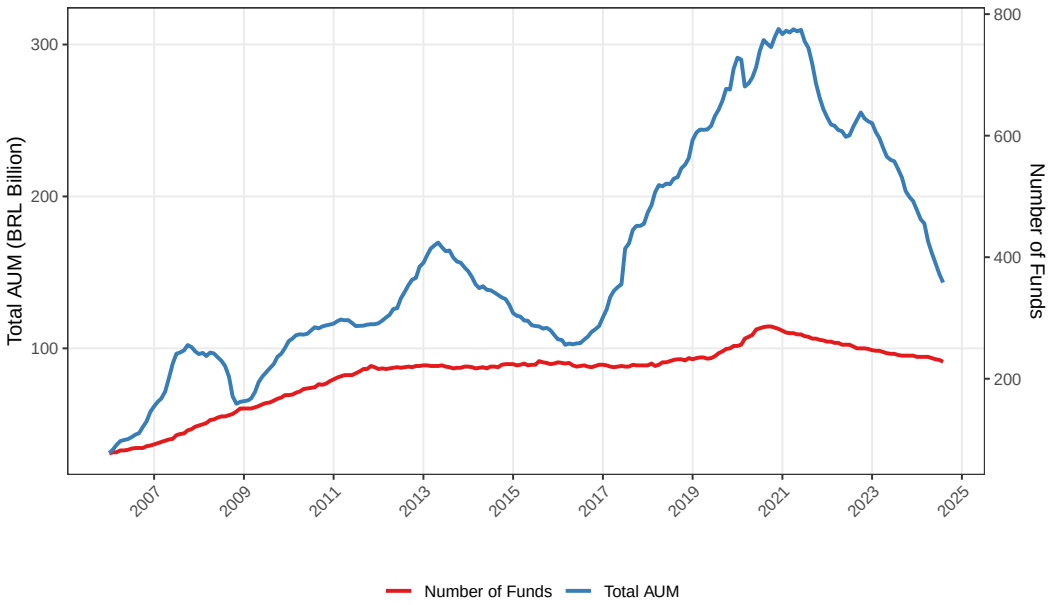
Notes: This table reports the evolution of Brazilian macro hedge fund characteristics over time. The number of funds corresponds to those active in December of each year (or August 2024 which is the last month in our sample). Average return is the NAV weighted excess return of all funds. Total AUM is measured in billions of BRL, while the median AUM per fund is presented in millions. The performance and management fees are expressed as percentages. All AUM figures are inflation-adjusted using the Brazilian IPCA index (base date: August 2024).

Figure 1.1 illustrates the time-series evolution of total assets under management alongside the number of active funds. The figure reveals strong growth through 2020, followed by contraction in both fund count and total AUM. This pattern reflects both the development and consolidation phases of Brazil's hedge fund industry.

1.3.2 Risk Factors

Hedge fund risk exposures are estimated with respect to seven factors designed to capture the major sources of systematic risk in Brazilian and global markets. The risk factors include:

Figure 1.1: Total AUM of sampled macro hedge funds (2006-2024)



Note: This figure presents the number of funds (right-hand scale) and total assets under management (left-hand scale) of sampled macro hedge funds over time, adjusted for inflation (base date: August 2024).

- **BXMKT**: Brazilian equity market exposure, proxied by the BOVESPA index futures (IND). Positions are rolled to the nearest expiration to maintain continuous exposure.
- **USD**: BRL/USD exchange rate exposure, constructed from rolling positions in BRL/USD futures (DOL). A positive return on this factor corresponds to BRL depreciation (USD appreciation).
- **BXBOND1Y**: Brazilian 1-year nominal interest rate exposure, constructed from rolling positions in interbank deposit futures (DI1) with target maturity of 1 year. At each point in time, the contract closest to 1-year maturity is selected.
- **BXBOND5Y**: Brazilian 5-year nominal interest rate exposure, constructed analogously to BXBOND1Y but targeting 5-year maturity.
- **BXINF5Y**: Brazilian 5-year inflation-linked bond exposure, constructed from rolling positions in inflation-linked government bonds (NTN-B) with target maturity of 5 years.
- **USMKT**: US equity market exposure, measured by the S&P 500 index.
- **USBOND5Y**: US 5-year nominal bond exposure, constructed from daily market yields reported by the Federal Reserve, converted to a bond

return index. USMKT and USBOND5Y are the only non-tradable factor in the set.

With the exception of USMKT and USBOND5Y, all risk factors represent tradable strategies accessible to Brazilian hedge funds. The construction ensures that the estimated exposures correspond to positions funds could actually implement. Returns on USMKT and USBOND5Y are computed in US dollars, while all other factors are in Brazilian reais. Table 1.2 presents summary statistics for the risk factors over the January 2006 to August 2024 sample period.

Table 1.2: Descriptive statistics of risk factors

Risk Factor	Description	Mean (%)	Std. Dev. (%)	Sharpe Ratio	Min (%)	Max (%)
BXMKT	Brazilian BOVESPA Index Future (IND)	2.35	22.46	0.10	-30.30	16.11
USD	BRL/USD Exchange Rate Future (DOL)	-0.81	15.82	-0.05	-12.04	17.95
BXBOND1Y	Interest Rate Future (DI1) - 1-Year Constant Maturity	0.94	1.47	0.64	-2.38	2.19
BXBOND5Y	Interest Rate Future (DI1) - 5-Year Constant Maturity	2.93	10.18	0.29	-12.86	15.68
BXINF5Y	Brazilian Inflation-Linked Bonds - 5-Year Target Maturity	3.36	6.16	0.55	-7.48	7.69
USMKT	S&P 500 Index	8.23	15.05	0.55	-17.02	12.68
USBOND5Y	US Bonds - 5-Year Constant Maturity	1.02	4.18	0.24	-3.50	3.78

Notes: This table reports summary statistics for risk factors: mean return, standard deviation, sharpe ratio, minimum (Min), and maximum (Max) returns. Mean return and standard deviation are expressed as yearly percentages, while Min and Max are monthly values. US bond returns are computed using data from the Federal Reserve. Returns for USMKT and USBOND5Y are computed in USD. Data was computed from monthly return data from January 2006 to August 2024.

Table 1.3 reports pairwise correlations among the risk factors.

Table 1.3: Risk factor correlation

	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y	USMKT	USBOND5Y
BXMKT	1.00						
USD	-0.67	1.00					
BXBOND1Y	0.21	-0.18	1.00				
BXBOND5Y	0.45	-0.44	0.76	1.00			
BXINF5Y	0.40	-0.44	0.63	0.72	1.00		
USMKT	0.59	-0.43	-0.03	0.18	0.16	1.00	
USBOND5Y	-0.15	0.12	0.24	0.19	0.11	-0.08	1.00

Notes: This table reports the correlation matrix of risk factors. Data was computed from monthly return data from January 2006 to August 2024.

To explore the intuition that hedge fund exposures to these risk factors may predict inflation, Table 1.4 reports correlations between risk factor returns and 12-month IPCA forecast surprises (defined as realized cumulative 12-month inflation minus the FOCUS forecast made 12 months prior).

Table 1.4: Correlation between risk factors and 12-month IPCA forecast errors

Risk factor	Correlation
Brazilian Equity Market	-0.224
1Y Brazilian Nominal Bond	-0.622
5Y Brazilian Nominal Bond	-0.606
5Y Brazilian Inflation-Linked Bond	-0.267
BRL/USD Exchange Rate	0.066

Note: This table presents the correlation of risk factors with inflation 12-month expectation errors. Expectation error is rolling 12-month realized inflation minus the FOCUS forecast 12 months prior

1.3.3 Inflation and Forecasts

The target variable for forecasting is monthly inflation measured by the IPCA (Índice de Preços ao Consumidor Amplo), Brazil's official consumer price index produced by IBGE (Instituto Brasileiro de Geografia e Estatística). IPCA is the index targeted by Brazil's Central Bank for monetary policy purposes and is the most widely monitored inflation measure. The forecasting exercise focuses on predicting inflation 1 to 12 months ahead, as well as cumulative inflation over 3-month, 6-month, and 12-month horizons.

The benchmark forecast against which all models are compared is the FOCUS forecast, a weekly survey of professional forecasters conducted by the Brazilian Central Bank. FOCUS aggregates expectations from major financial institutions, market participants, and consulting firms. The median FOCUS forecast is published and serves as a widely-used measure of market consensus. For this analysis, We use the monthly median FOCUS forecast for inflation at various horizons. FOCUS forecasts are real-time: the forecast used for month t reflects information available only through that date, avoiding any look-ahead bias.

The out-of-sample forecasting period runs from August 2016 to August 2024, generating 97 forecasts for the 1-month horizon and 86 forecasts for the 12-month horizon (declining due to the terminal date constraint). The choice of August 2016 as the start date allows for a minimum 10-year in-sample training period for the machine learning models, balancing the need for sufficient data to estimate parameters against the desire for a reasonably long out-of-sample evaluation period.

Additional high-dimensional predictors used in the adaptive LASSO and random forest forecasts are described in Appendix 1.B. These predictors encompass a broad set of 70+ macroeconomic and financial variables commonly

employed in Brazilian inflation forecasting (Garcia *et al.*, 2017; Medeiros *et al.*, 2021), including lagged inflation, price indexes, monetary aggregates, commodity prices, measures of economic activity, employment, interest rates, exchange rates, equity indexes, and credit aggregates.

1.4 Methodology

1.4.1 Estimating Time-Varying Risk Exposures

We denote fund i's excess return at time t as $r_{i,t}$, and let $\mathbf{f}_t = (f_{1,t}, f_{2,t}, \ldots, f_{K,t})'$ represent the K risk factor returns, where $K = 7$ in our application. The relationship between fund returns and factor exposures is specified as:

$$r_{i,t} = \alpha_{i,t} + \boldsymbol{\beta}'_{i,t}\mathbf{f}_t + \varepsilon_{i,t} \tag{1.1}$$

where $\boldsymbol{\beta}_{i,t} = (\beta_{i,1,t}, \beta_{i,2,t}, \ldots, \beta_{i,K,t})'$ is the vector of time-varying factor loadings for fund i, $\alpha_{i,t}$ is the fund's time-varying alpha, and $\varepsilon_{i,t}$ is an idiosyncratic error term. Following Bollen & Whaley (2009), we consider two distinct alternatives to model how time-varying betas $\boldsymbol{\beta}_{i,t}$ evolve: a state-space model with stochastic and mean-reverting factor loadings and a structural break model in which factor loadings are allowed to change infrequently and discretely.

1.4.2 State-Space Model

The state-space approach treats factor loadings and fund alpha as latent state variables that evolve stochastically over time. This specification assumes that hedge fund risk exposures adjust smoothly and gradually in response to changing market conditions and investment opportunities. The model consists of an observation equation linking observed returns to unobserved states and a state equation governing the dynamic evolution of these states.

The **observation equation** is:

$$r_{i,t} = \alpha_{i,t} + \boldsymbol{\beta}'_{i,t}\mathbf{f}_t + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim N(0, \sigma^2_{\varepsilon,i}) \tag{1.2}$$

We allow the state vector to include both alpha and betas, defining $\boldsymbol{\theta}_{i,t} = (\alpha_{i,t}, \boldsymbol{\beta}'_{i,t})'$. The **state equation** specifies that this augmented state vector follows a stationary VAR(1) process:

$$\boldsymbol{\theta}_{i,t} = \boldsymbol{\mu}_i + \boldsymbol{\Phi}_i(\boldsymbol{\theta}_{i,t-1} - \boldsymbol{\mu}_i) + \boldsymbol{\eta}_{i,t}, \quad \boldsymbol{\eta}_{i,t} \sim N(\mathbf{0}, \mathbf{Q}_i) \tag{1.3}$$

where $\boldsymbol{\mu}_i$ is a $(K+1)\times 1$ vector of long-run mean states, $\boldsymbol{\Phi}_i$ is a $(K+1)\times(K+1)$ autoregressive matrix governing the persistence of deviations from the mean,

and $\mathbf{Q}_i$ is a $(K+1)\times(K+1)$ covariance matrix of innovations. This specification allows alpha and betas to exhibit mean reversion while permitting smooth time-variation in fund positioning.

The fixed parameters $(\boldsymbol{\mu}_i, \boldsymbol{\Phi}_i, \mathbf{Q}_i, \sigma^2_{\varepsilon,i})$ are estimated by maximum likelihood in conjunction with the Kalman filter. The log-likelihood function is:

$$\log L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left[\log(F_t) + \frac{v_t^2}{F_t}\right] \tag{1.4}$$

where $v_t = r_{i,t} - \alpha_{i,t|t-1} - \boldsymbol{\beta}'_{i,t|t-1}\mathbf{f}_t$ is the one-step-ahead forecast error, F_t is the variance of the forecast error, and $\boldsymbol{\theta}_{i,t|t-1} = (\alpha_{i,t|t-1}, \boldsymbol{\beta}'_{i,t|t-1})'$ is the predicted state given information up to $t-1$. The Kalman filter recursively updates the state estimate $\boldsymbol{\theta}_{i,t|t}$ and its covariance matrix $\mathbf{P}_{i,t|t}$ as new observations arrive, providing optimal filtered estimates of the time-varying parameters conditional on all information available through time t.

For each month-end beginning in June 2006, we estimate the model for each fund with at least 100 daily return observations using all available data up to $t-5$. This five-day lag ensures that the estimation uses only information that was genuinely available to market participants at month-end, as Brazilian regulation mandates fund return disclosure within two business days. The filtered estimates $\boldsymbol{\theta}_{i,t|t}$ obtained from the final Kalman filter iteration at time t represent the predicted exposures as of month-end, incorporating all data through $t-5$ and the factor realizations at time t.

1.4.3 Structural Break Model

The structural break model estimated via optimal changepoint regression provides an alternative framework that permits discrete breaks in factor loadings. This approach is particularly suitable when hedge funds adjust exposures abruptly in response to regime changes or portfolio reallocations, rather than through smooth and continuous rebalancing. Following Bollen & Whaley (2009), the model partitions each fund's sample into $M+1$ regimes with unknown breakpoints, estimating constant parameters within each regime:

$$r_{i,t} = \alpha_{i,m} + \boldsymbol{\beta}'_{i,m}\mathbf{f}_t + \varepsilon_{i,t}, \quad t \in [T_{m-1}+1, T_m] \tag{1.5}$$

where $T_0 = 0 < T_1 < T_2 < \cdots < T_M = T$ denote the breakpoints and $(\alpha_{i,m}, \boldsymbol{\beta}_{i,m})$ are the parameters in regime m.

The breakpoints and regime-specific parameters are estimated by minimizing the sum of squared residuals over all possible partitions. For a given number of breaks M, the optimal changepoints are:

$$\left(\hat{T}_1, \ldots, \hat{T}_M, \hat{\alpha}_{i,1}, \ldots, \hat{\alpha}_{i,M+1}, \hat{\boldsymbol{\beta}}_{i,1}, \ldots, \hat{\boldsymbol{\beta}}_{i,M+1}\right) = \underset{\{T_m, \alpha_{i,m}, \boldsymbol{\beta}_{i,m}\}}{\arg\min} \sum_{m=1}^{M+1} \sum_{t=T_{m-1}+1}^{T_m} \left(r_{i,t} - \alpha_{i,m} - \boldsymbol{\beta}_{i,m}' \mathbf{f}_t\right)^2. \tag{1.6}$$

The number of breaks is selected using the Bayesian Information Criterion (BIC), which balances model fit against the cost of additional parameters. We sequentially test specifications with $M = 0, 1, 2$ breaks, selecting the model that minimizes BIC.

For each month-end beginning in June 2006, we apply the optimal changepoint regression to each fund with at least 100 daily return observations. When a fund has more than 252 daily observations (approximately one trading year), we restrict the estimation to the most recent 252 observations to focus on recent positioning dynamics and enhance computational efficiency. We allow for a maximum of two breakpoints, yielding at most three distinct regimes per fund. The estimated exposures $\hat{\boldsymbol{\beta}}_{i,t}$ for month t correspond to the regime-specific loadings of the regime to which time t belongs, using data available only through $t - 5$ business days to maintain consistency with the state-space estimation timing.

1.5 Results

To validate the estimated exposures, we assess their ability to explain variation in future hedge fund returns. Table 1.5 reports R^2 statistics from regressions of actual fund excess returns on predicted returns based on lagged estimated exposures and fund alpha. The mean fund-level R^2 is 0.28 for the changepoint method and 0.30 for the Kalman filter, indicating that the models capture a meaningful fraction of return variation. The pooled R^2 (treating all fund-month observations as a single regression) is 0.37-0.38, and the aggregate R^2 (using NAV-weighted aggregate returns) reaches 0.50-0.52. These validation statistics confirm that both methods produce sensible exposure estimates that explain hedge fund returns, lending confidence to their use as predictors of inflation.

Bollen & Whaley (2009) compare the structural break specification to the state-space model through simulation exercises designed to evaluate each method's power to detect time-variation in hedge fund risk exposures. The conceptual distinction between the two approaches lies in the dynamics of exposure adjustment: the state-space model assumes gradual, mean-reverting changes in parameters, while the structural break model allows for abrupt, permanent shifts. Through Monte Carlo experiments using sample sizes and

Table 1.5: Macro hedge fund variance explained by estimated risk exposures

Statistic	Structural break model	State-space model
Mean R^2	0.28	0.30
Median R^2	0.22	0.28
Pooled R^2	0.37	0.38
Aggregate R^2	0.52	0.50

Notes: This table reports the degree to which estimated returns (based on lagged estimated risk exposures and fund alpha) explain actual excess returns. Mean R^2 and Median R^2 are calculated at the fund level. Pooled R^2 treats all fund-month observations as a single regression. Aggregate R^2 uses NAV-weighted aggregate returns and risk exposure estimates.

return dynamics comparable to those observed in hedge fund data, Bollen & Whaley (2009) find that the optimal changepoint regression exhibits greater power in rejecting the null hypothesis of constant exposures when parameter changes are infrequent but sizable. Consistent with these findings, we adopt the optimal changepoint regression as our primary estimation procedure, while also estimating the parameters of the state-space model with mean-reverting stochastic betas as a robustness check.

1.5.1 Aggregation

We then aggregate fund-level risk exposure estimate from the optimal changepoint method into industry-level risk exposure variables:

$$\text{HFRE}_{k,t} = \sum_{i=1}^{N_t} w_{i,t} \hat{\beta}_{i,k,t} \tag{1.7}$$

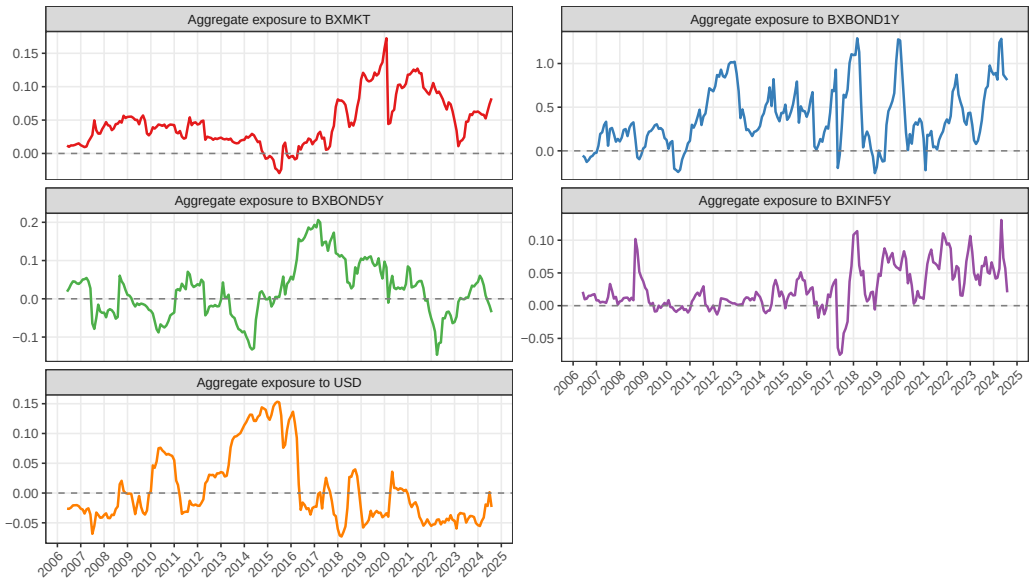
where $w_{i,t} = \text{NAV}_{i,t} / \sum_{j=1}^{N_t} \text{NAV}_{j,t}$ are NAV-based weights, N_t is the number of active funds meeting the data requirements in month t, and k indexes the risk factor. This produces seven aggregate HFRE series—one for each risk factor—capturing the value-weighted average positioning of the hedge fund industry.

The resulting panel of estimated risk exposures spans June 2006 to August 2024, covering all funds that meet the minimum data threshold of 100 daily observations in each month.

Figure 1.2 plots the time-series of estimated aggregate exposures. The exposures exhibit sensible time variation. For instance, aggregate exposure to BXMKT drops abruptly from around 0.17 to 0.05 immediately after the COVID shock.

Figure 1.3 presents the cross-sectional standard deviation of estimated exposures, measuring disagreement or dispersion in hedge fund positioning.

Figure 1.2: Evolution of estimated risk exposure



Note: This figure presents the time-series of the estimated aggregate macro hedge fund exposure to risk factors.

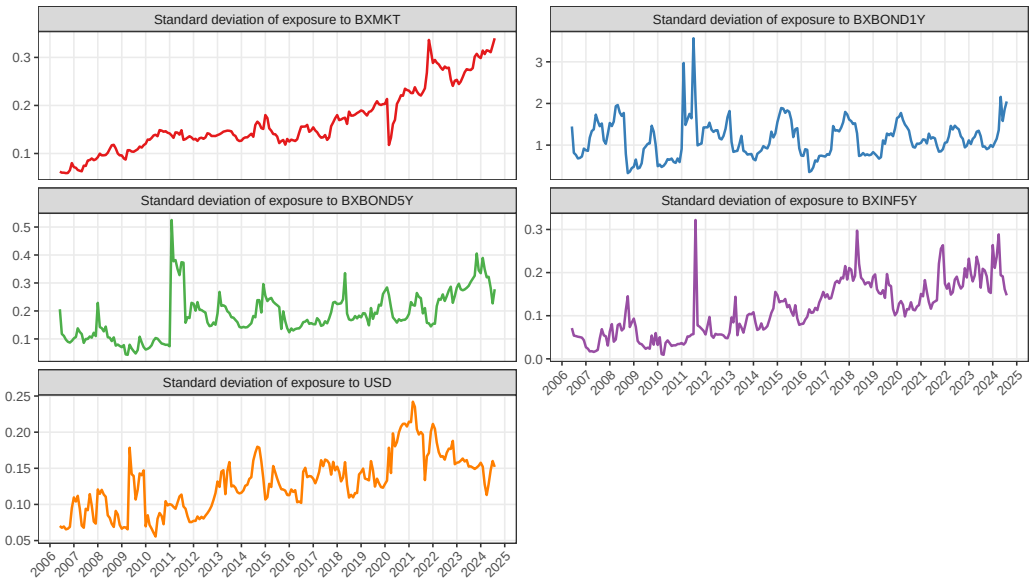
Higher dispersion indicates greater heterogeneity in views or strategies across funds. Dispersion varies over time for all factors, with pronounced spikes during episodes such as the 2008 financial crisis, the 2015-2016 Brazilian recession, and the COVID-19 pandemic. This heterogeneity motivates aggregating exposures at the industry level while recognizing that individual funds maintain diverse strategies.

1.5.2 Hedge Fund Risk Exposures and Inflation: In-Sample Evidence

We then examine the in-sample relationship between hedge fund risk exposures and future inflation, conditioning on FOCUS forecasts. Table 1.6 reports results from regressing realized cumulative inflation at horizons of 3, 6, 9, and 12 months on the FOCUS forecast (for the appropriate horizon) and the seven HFRE variables. This regression directly tests whether hedge fund positioning contains predictive information beyond the professional consensus.

At short horizons (3 months), the FOCUS forecast dominates with a highly significant coefficient of 1.29 (t-statistic = 11.85), and none of the HFRE variables achieve statistical significance. As the horizon extends, however, the FOCUS forecast loses explanatory power: the coefficient declines to 1.10 at 6 months (t-statistic = 4.95), 0.63 at 9 months (t-statistic = 1.55), and 0.18

Figure 1.3: Evolution of cross-sectional volatility of estimated risk exposures



Note: This figure presents the time-series of the cross-sections volatility of estimated exposures to risk factors.

at 12 months (t-statistic = 0.51, insignificant). In contrast, the coefficient on USDRE increases monotonically across horizons, reaching 0.21 at 12 months with a t-statistic of 2.05, significant at the 5% level.

This 12-month coefficient of 0.21 implies that a one-unit increase in aggregate hedge fund USD exposure - roughly corresponding to a fund-level portfolio shift from neutral to fully hedged - predicts 21 basis points higher cumulative inflation over the next year.

Importantly, USDRE retains significance even after controlling for the FOCUS forecast, indicating that hedge fund positioning conveys information not already incorporated in professional expectations. However, the other HFRE variables tested (BXMKTRE, BXBOND1YRE, BXBOND5YRE, BXINF5YRE) do not achieve statistical significance at any horizon, suggesting that USD exposure is the primary channel through which hedge fund positioning predicts inflation. This finding motivates our decision to focus on USDRE when augmenting out-of-sample forecasting models, rather than including all seven HFRE variables indiscriminately.

The predictive power of USDRE for Brazilian inflation is intuitive given the country's economic history. Brazil has experienced recurring episodes of elevated inflation and currency instability, establishing a deeply ingrained relationship between inflation expectations and exchange rate movements. However, this relationship raises important questions about external validity.

Table 1.6: Regression of cumulative inflation on FOCUS forecasts and macro hedge fund risk exposure data

Variable	3M	6M	9M	12M
Intercept	**-0.00**	-0.00	0.01	0.04
	(-2.41)	(-0.43)	(0.74)	(1.88)
FOCUS Forecast	**1.29**	**1.10**	0.63	0.18
	(11.85)	**(4.95)**	(1.55)	(0.51)
BXMKTRE	0.04	0.08	0.14	0.21
	(1.84)	(0.77)	(0.67)	(0.78)
BXBOND1YRE	-0.00	-0.01	-0.01	-0.00
	(-0.59)	(-0.86)	(-0.66)	(-0.12)
BXBOND5YRE	-0.00	-0.01	-0.03	-0.06
	(-0.33)	(-0.25)	(-0.57)	(-1.29)
BXINF5YRE	-0.00	0.06	0.05	-0.00
	(-0.15)	(1.18)	(0.92)	(-0.06)
USDRE	0.01	0.06	0.14	**0.21**
	(0.98)	(1.35)	(1.66)	**(2.05)**
R^2	0.69	0.51	0.40	0.42
Observations	224	224	224	224

Note: This table presents estimated coefficients from linear regressions in which the dependent variable are the cumulative inflation (multiplied by a factor of 100) over selected horizons - 3, 6, 9 and 12 months ahead - and the independent variables are the FOCUS forecast for the appropriate horizon and the macro hedge fund estimated risk exposures to BXMKT, BXBOND1Y, BXBOND5Y, BXINF5Y and USD. Newey-West adjusted t-statistics are presented between parentheses. Bold indicates |t-stat| > 1.96.

The predictive power of USDRE may be specific to emerging market economies with a history of high and volatile inflation, where the exchange rate serves as a critical barometer of macroeconomic stress. In developed economies with well-anchored inflation expectations and deep currency markets, the connection between hedge fund currency positioning and future inflation may be substantially weaker or altogether absent. Future research should investigate whether similar patterns emerge in other inflation-prone emerging markets or if the Brazilian case represents a unique institutional and historical case.

1.5.3 Pseudo Out-of-Sample Inflation Forecasting with USDRE

Having established that USDRE predicts inflation in-sample, particularly at longer horizons, we now evaluate whether incorporating HFRE data improves out-of-sample forecasting accuracy.

Let y_{t+h} denote inflation realized h months after month t. We consider forecasts for individual monthly inflation ($h = 1, 2, \ldots, 12$) as well as cumulative inflation over 3, 6, and 12 months. The following forecasting procedures are evaluated:

1. FOCUS: The median consensus forecast from FOCUS, serving as the primary benchmark.

2. FOCUS with bias correction: Adjusts the FOCUS forecast for systematic biases estimated from in-sample forecast errors. Following Mincer & Zarnowitz (1969), we estimate the regression:

$$y_{t+h} = \delta_0 + \delta_1 \text{FOCUS}_{t,h} + \xi_{t+h} \tag{1.8}$$

and construct the bias-corrected forecast as $\hat{y}^{BC}_{t+h|t} = \hat{\delta}_0 + \hat{\delta}_1 \text{FOCUS}_{t,h}$. This procedure corrects for systematic over- or under-prediction in professional forecasts.

3. OLS plus USDRE: A parsimonious linear regression:

$$y_{t+h} = \gamma_0 + \gamma_1 \text{FOCUS}_{t,h} + \gamma_2 \text{USDRE}_t + u_{t+h} \tag{1.9}$$

where $\text{FOCUS}_{t,h}$ is the FOCUS forecast for horizon h made at time t, and USDRE_t is the aggregate hedge fund exposure to USD. This specification isolates the incremental predictive power of hedge fund USD positioning beyond the professional consensus.

4. Adaptive LASSO: A penalized regression method that handles large predictor sets by shrinking coefficients toward zero, with the degree of shrinkage determined by cross-validation (Zou, 2006). The adaptive LASSO has been shown to perform well for Brazilian inflation forecasting (Garcia *et al.*, 2017). The predictor set includes 64 macroeconomic and financial variables (with lags as specified in Appendix 1.B), encompassing lagged inflation, price indexes, monetary aggregates, commodity prices, measures of economic activity, employment, interest rates, exchange rates, equity indexes, and credit aggregates.

5. Adaptive LASSO plus USDRE: Augments the adaptive LASSO by adding hedge fund risk exposure variables to the predictor set. Specifically, we include contemporaneous and lagged values (up to 2 lags) of all seven USDRE, its first difference and its cross-sectional dispersion, allowing the adaptive LASSO algorithm to select which USDRE related variables and at which lags, if any, can improve forecasting accuracy.

6. Random Forest: A nonparametric ensemble method that constructs multiple decision trees and averages their predictions (Breiman, 2001). The intuition behind random forests is to exploit the wisdom of crowds: each tree is trained on a bootstrapped sample of the data and considers only a random subset of predictors at each split, reducing correlation among trees and improving out-of-sample performance. The ensemble average mitigates overfitting while capturing nonlinear relationships and interactions among predictors. Random

forests have demonstrated strong performance for Brazilian inflation forecasting (Medeiros *et al.*, 2021). The predictor set mirrors that of the adaptive LASSO (64 macroeconomic variables).

7. Random Forest plus USDRE: Augments the random forest by including contemporaneous and lagged values (up to 2 lags) of USDRE, its first difference and its cross-sectional dispersion.

All forecasting procedures are estimated using an expanding window approach. The initial in-sample period spans August 2006 to July 2016, providing 120 months of data for parameter estimation and model training. For each subsequent month t from August 2016 onward, the model is re-estimated using all data through month t, and forecasts $\hat{y}_{t+h|t}$ are generated for horizons $h = 1, 2, \ldots, 12$. This recursive procedure ensures that all forecasts are truly out-of-sample, using only information available at the forecast date. Forecasts for the cumulative 3, 6 and 12 months ahead are computed by adding the individual monthly forecasts.

Forecast accuracy is measured using root mean squared error (RMSE) and mean absolute error (MAE), defined as:

$$\text{RMSE}_h = \sqrt{\frac{1}{T_{\text{OOS}}} \sum_{t \in \mathcal{T}_{\text{OOS}}} (y_{t+h} - \hat{y}_{t+h|t})^2}, \quad \text{MAE}_h = \frac{1}{T_{\text{OOS}}} \sum_{t \in \mathcal{T}_{\text{OOS}}} |y_{t+h} - \hat{y}_{t+h|t}| \tag{1.10}$$

where $\mathcal{T}_{\text{OOS}}$ denotes the out-of-sample evaluation period (August 2016 to August 2024) and T_{OOS} is the number of out-of-sample forecasts (97 for $h = 1$, declining to 86 for $h = 12$). RMSE penalizes large errors more heavily due to its quadratic form, making it sensitive to outliers, while MAE treats all errors linearly and is more robust to extreme forecast misses. Analyzing both metrics provides a comprehensive assessment of forecasting performance across different error magnitudes.

To test whether any forecasting procedure achieves statistically lower forecast errors than the FOCUS benchmark, we employ the one-sided Diebold-Mariano test (Diebold & Mariano, 1995), the standard approach for evaluating comparative forecast accuracy.

Tables 1.7 and 1.8 present RMSE and MAE for all forecasting procedures over the August 2016 to August 2024 evaluation period, covering individual monthly horizons ($h = 1, \ldots, 12$) and cumulative horizons (3, 6, and 12 months).

Tables 1.7 and 1.8 present RMSE and MAE for all forecasting models over the August 2016 to August 2024 evaluation period, covering individual monthly horizons ($h = 1, \ldots, 12$) and cumulative horizons (3, 6, and 12 months).

Table 1.7: Pseudo out-of-Sample RMSE for inflation forecasts incorporating macro hedge fund risk exposure data

	Inflation h months ahead - RMSE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	12.13	30.75	39.80	**40.83**	41.14	41.63	43.18	43.51	43.69	43.70	43.91	42.60	66.01	139.59	273.77
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	11.34**	**29.61****	40.02	40.84	**41.05**	41.53	42.92	43.25	43.42	43.38	43.56	42.40	**63.59***	**136.22**	262.10
	(0.93)	(0.96)	(1.01)	(1.00)	(1.00)	(1.00)	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(1.00)	(0.96)	(0.98)	(0.96)
OLS plus USDRE	**11.31****	29.75*	40.11	40.93	41.06	41.22	42.53*	42.78*	43.01	43.00	**43.24**	**42.20**	63.79*	137.05	258.08*
	(0.93)	(0.97)	(1.01)	(1.00)	(1.00)	(0.99)	(0.98)	(0.98)	(0.98)	(0.98)	(0.98)	(0.99)	(0.97)	(0.98)	(0.94)
Adaptive LASSO	12.12	30.01	**39.34**	41.09	41.58	41.37	42.07	42.74	43.41	43.46	43.63	42.93	64.76	137.02	245.93
	(1.00)	(0.98)	(0.99)	(1.01)	(1.01)	(0.99)	(0.97)	(0.98)	(0.99)	(0.99)	(0.99)	(1.01)	(0.98)	(0.98)	(0.90)
Adaptive LASSO plus USDRE	12.12	29.90	39.77	41.05	42.04	41.85	41.87*	42.56	43.52	43.29	43.25	42.93	65.20	138.88	244.62*
	(1.00)	(0.97)	(1.00)	(1.01)	(1.02)	(1.01)	(0.97)	(0.98)	(1.00)	(0.99)	(0.98)	(1.01)	(0.99)	(0.99)	(0.89)
Random Forest	21.48	33.46	40.61	42.20	42.06	41.46	**41.60**	**41.45**	**42.14**	**42.60**	44.12	43.62	74.21	144.68	245.72
	(1.77)	(1.09)	(1.02)	(1.03)	(1.02)	(1.00)	(0.96)	(0.95)	(0.96)	(0.97)	(1.00)	(1.02)	(1.12)	(1.04)	(0.90)
Random Forest plus USDRE	21.60	33.42	40.59	41.54	41.80	**41.17**	41.66	41.74	42.44	43.12	44.14	43.49	73.89	142.43	**243.43**
	(1.78)	(1.09)	(1.02)	(1.02)	(1.02)	(0.99)	(0.96)	(0.96)	(0.97)	(0.99)	(1.01)	(1.02)	(1.12)	(1.02)	(0.89)

Notes: Total of 97 ($h = 1$) to 86 ($h = 12$) forecasts covering the period between August 2016 and August 2024. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest RMSE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

Table 1.8: Pseudo out-of-Sample MAE for inflation forecasts incorporating macro hedge fund risk exposure data

	Inflation h months ahead - MAE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	9.12	21.90	**28.30**	**29.39**	29.74	30.53	32.23	32.43	32.73	32.49	32.56	**31.63**	50.57	107.52	177.26
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	**8.82**	**21.61**	29.40	30.21	30.48	31.11	32.65	32.85	32.90	32.63	32.55	31.92	50.22	**106.43**	184.12
	(0.97)	(0.99)	(1.04)	(1.03)	(1.02)	(1.02)	(1.01)	(1.01)	(1.01)	(1.00)	(1.00)	(1.01)	(0.99)	(0.99)	(1.04)
OLS plus USDRE	8.87	21.75	28.81	29.73	30.04	30.54	32.02	32.32	32.61	32.46	**32.53**	31.82	**49.77**	106.70	**171.52**
	(0.97)	(0.99)	(1.02)	(1.01)	(1.01)	(1.00)	(0.99)	(1.00)	(1.00)	(1.00)	(1.00)	(1.01)	(0.98)	(0.99)	(0.97)
Adaptive LASSO	9.29	21.84	29.41	30.70	30.69	30.81	31.97	32.56	33.24	33.12	33.69	33.30	50.30	107.00	184.07
	(1.02)	(1.00)	(1.04)	(1.04)	(1.03)	(1.01)	(0.99)	(1.00)	(1.02)	(1.02)	(1.03)	(1.05)	(0.99)	(1.00)	(1.04)
Adaptive LASSO plus USDRE	9.29	21.81	29.24	30.45	30.89	31.34	31.78	32.52	33.43	33.11	33.26	33.30	50.01	108.57	181.74
	(1.02)	(1.00)	(1.03)	(1.04)	(1.04)	(1.03)	(0.99)	(1.00)	(1.02)	(1.02)	(1.02)	(1.05)	(0.99)	(1.01)	(1.03)
Random Forest	15.69	25.06	30.11	30.88	30.52	30.12	30.75	**30.85**	**31.17**	**31.69**	32.74	32.75	57.99	112.38	175.53
	(1.72)	(1.14)	(1.06)	(1.05)	(1.03)	(0.99)	(0.95)	(0.95)	(0.95)	(0.98)	(1.01)	(1.04)	(1.15)	(1.05)	(0.99)
Random Forest plus USDRE	15.71	24.91	29.49	29.77	**29.67**	**29.76**	**30.41***	31.00	31.39	32.22	32.71	32.51	57.10	108.79	177.91
	(1.72)	(1.14)	(1.04)	(1.01)	(1.00)	(0.97)	(0.94)	(0.96)	(0.96)	(0.99)	(1.00)	(1.03)	(1.13)	(1.01)	(1.00)

Notes: Total of 97 ($h = 1$) to 86 ($h = 12$) forecasts covering the period between August 2016 and August 2024. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest MAE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

Tables 1.7 and 1.8 reveal a consistent pattern: forecasts that incorporate USDRE systematically outperform their counterparts that do not, with improvements concentrated at medium to long horizons.

The most policy-relevant result concerns cumulative 12-month inflation forecasts. In terms of RMSE, only forecasting procedures that incorporate USDRE achieve statistically significant improvements over the FOCUS benchmark at the 10% level. OLS plus USDRE reduces RMSE relative to FOCUS by 2% (significant at 10%), while FOCUS with bias correction fails to achieve statistical significance. Similarly, Adaptive LASSO plus USDRE beats FOCUS at the 10% significance level, whereas the standard Adaptive LASSO without USDRE does not achieve significance. In terms of MAE, OLS plus USDRE achieves the lowest forecast error across all methods, representing a 3% reduction relative to FOCUS (although not significant at conventional levels).

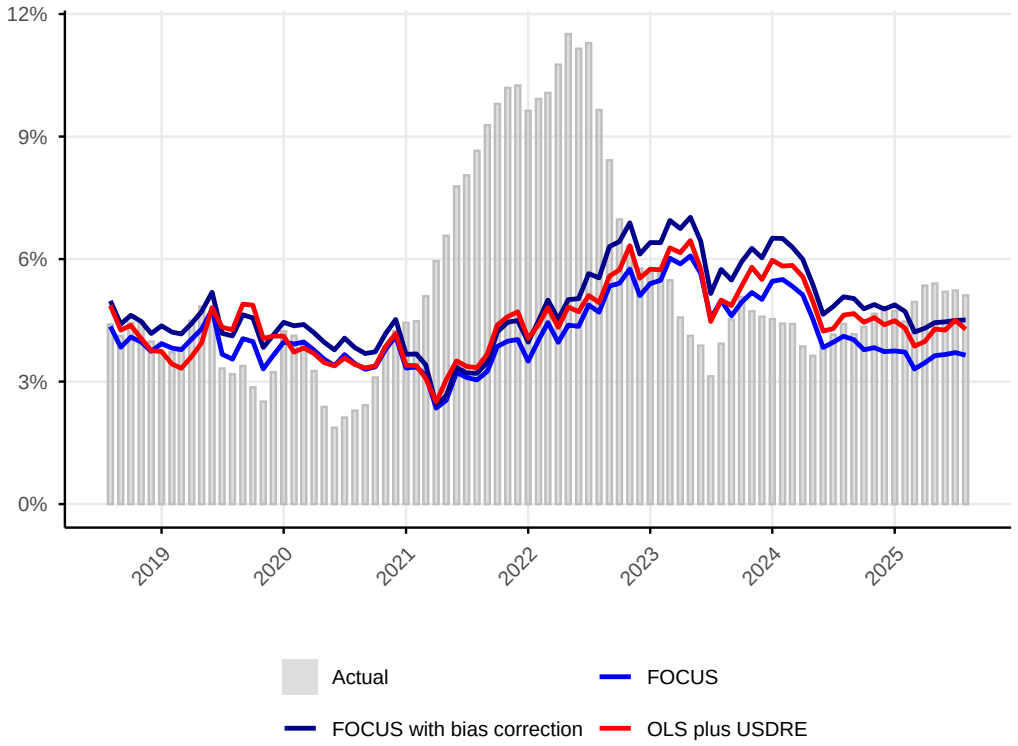
For individual monthly horizons, OLS plus USDRE demonstrates statistically significant improvements over FOCUS at horizons $h = 7$ and $h = 8$ (RMSE), while FOCUS with bias correction does not achieve significance at these horizons. The only instance where FOCUS with bias correction outperforms OLS plus USDRE occurs at $h = 2$ (RMSE), where bias correction achieves 5% significance while OLS plus USDRE reaches 10% significance. This pattern reinforces that USDRE's predictive power strengthens with forecast horizon.

At the 3-month and 6-month cumulative horizons, models incorporating USDRE continue to perform well, but results are mixed. Random Forest plus USDRE reduces RMSE and MAE relative to the standard Random Forest. However, that is not true for the forecasts using Adaptive LASSO methodology, suggesting that nonlinear methods may extract more value from HFRE data than linear high-dimensional methods for short to intermediate horizons.

Figure 1.4 plots realized rolling 12-month inflation against selected forecasts (FOCUS, FOCUS with bias correction, and OLS plus USDRE). The figure suggests that OLS plus USDRE anticipated inflation slightly more accurately during the 2021-2022 inflation surge, responding more quickly than the FOCUS benchmark. This visual evidence corroborates the statistical finding that incorporating hedge fund USD positioning improves forecast accuracy, particularly for longer-term inflation prediction.

To investigate if and how USDRE is being selected by the adaptive LASSO algorithms, Figure 1.5 and Figure 1.6 present heatmaps showing the frequency with which the Adaptive LASSO plus USDRE model selects USD risk exposure variables (at various lags) as positive or negative predictors across forecast horizons. The heatmaps reveal that USDRE variables are frequently

Figure 1.4: Cumulative 12-month inflation and selected forecasts



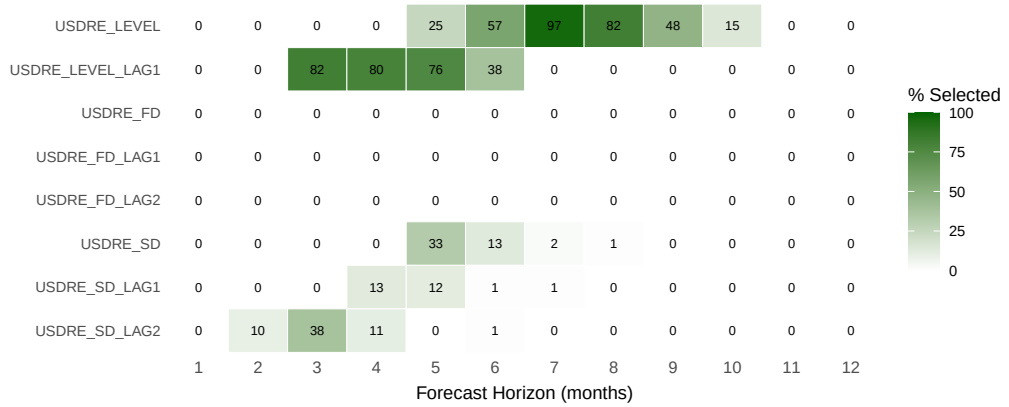
Note: Figure plots 12-month cumulative inflation selected forecasts - FOCUS, FOCUS with bias correction and OLS plus USDRE - and compares them with realized rolling 12-month inflation.

selected, especially for medium to long horizons (2-9 months), with positive coefficients dominating.

1.5.4 Conditioning on Inflation Uncertainty

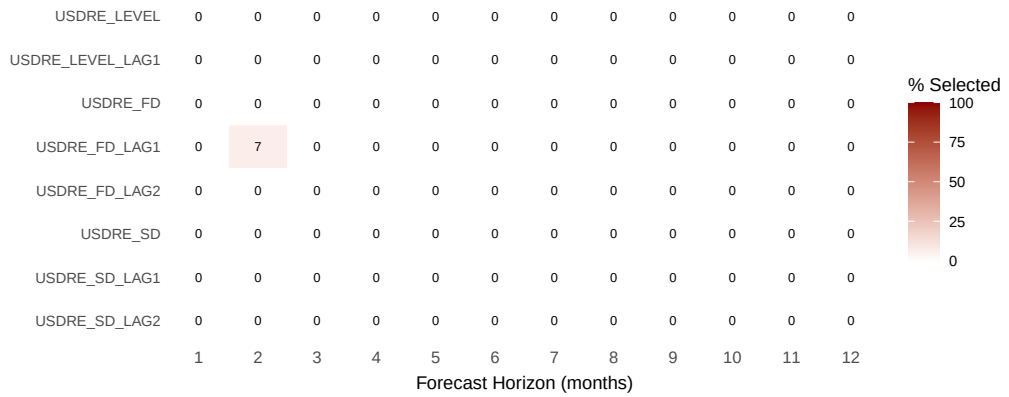
Motivated by (Cujean & Hasler, 2017), who propose a model in which return predictability is positovaly correlated with disagreement among market participants, we investigate how inflation forecasting performance varies across periods of high and low inflation uncertainty. To test this, we partition the out-of-sample period into high and low uncertainty regimes based on the cross-sectional standard deviation of FOCUS long-term inflation forecasts. Tables 1.9 and 1.10 report RMSE and MAE for the high-uncertainty subsample, while Tables 1.11 and 1.12 present results for low-uncertainty periods.

Figure 1.5: Adaptive LASSO plus USDRE - selection of USD risk exposure variables as positive predictors



Note: Figure presents the percentage of forecasts in which USD risk exposure variables were selected by the Adaptive LASSO plus USDRE specification with positive coefficients for each inflation horizon forecast.

Figure 1.6: Adaptive LASSO plus USDRE - selection of USD risk exposure variables as negative predictors



Note: Figure presents the percentage of forecasts in which USD risk exposure variables were selected by the Adaptive LASSO plus USDRE specification with negative coefficients for each inflation horizon forecast.

Table 1.9: Pseudo out-of-sample RMSE for inflation forecasts - high FOCUS uncertainty

	Inflation h months ahead - RMSE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	14.03	35.66	47.02	47.08	48.01	48.21	48.37	47.44	45.66	46.36	46.42	46.41	80.29	175.60	331.96
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	13.03*	**33.70****	46.91	46.56	47.48	47.89	48.07	47.24	45.29	45.98	45.95	46.34	**75.51****	169.97	319.55
	(0.93)	(0.94)	(1.00)	(0.99)	(0.99)	(0.99)	(0.99)	(1.00)	(0.99)	(0.99)	(0.99)	(1.00)	(0.94)	(0.97)	(0.96)
OLS plus USDRE	13.03*	34.11*	47.19	46.65	47.57	47.86	47.71	46.93	45.35	45.89	45.89	46.20	76.19*	170.40	316.36
	(0.93)	(0.96)	(1.00)	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(1.00)	(0.95)	(0.97)	(0.95)
Adaptive LASSO	13.95	33.83*	**45.96**	46.48	47.61	47.81	46.25*	46.81	45.36	45.33	44.80	46.29	77.12	**169.33**	291.43*
	(0.99)	(0.95)	(0.98)	(0.99)	(0.99)	(0.99)	(0.96)	(0.99)	(0.99)	(0.98)	(0.97)	(1.00)	(0.96)	(0.96)	(0.88)
Adaptive LASSO plus USDRE	13.95	33.84*	46.55	46.47	48.80	48.50	46.21**	46.57	45.85	44.97	**44.17**	46.29	77.91	172.75	291.66*
	(0.99)	(0.95)	(0.99)	(0.99)	(1.02)	(1.01)	(0.96)	(0.98)	(1.00)	(0.97)	(0.95)	(1.00)	(0.97)	(0.98)	(0.88)
Random Forest	25.16	37.23	46.51	**46.07**	**47.15**	**47.64**	**45.64**	**45.17**	**44.81**	**44.54**	45.52	46.70	87.73	173.14	**288.71***
	(1.79)	(1.04)	(0.99)	(0.98)	(0.98)	(0.99)	(0.94)	(0.95)	(0.98)	(0.96)	(0.98)	(1.01)	(1.09)	(0.99)	(0.87)
Random Forest plus USDRE	25.35	37.40	46.88	46.14	47.62	48.08	46.49	45.98	45.18	45.48	45.60	46.72	87.78	173.76	291.18
	(1.81)	(1.05)	(1.00)	(0.98)	(0.99)	(1.00)	(0.96)	(0.97)	(0.99)	(0.98)	(0.98)	(1.01)	(1.09)	(0.99)	(0.88)

Note: Table presents RMSE for forecasts covering months when FOCUS standard deviations of long-term inflation forecasts was above the sample period median. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest RMSE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

Table 1.10: Pseudo out-of-sample MAE for inflation forecasts - high FOCUS uncertainty

	Inflation h months ahead - MAE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	9.84	25.69	34.37	34.05	35.46	36.16	36.66	35.39	33.52	33.55	33.00	**33.50**	61.96	142.76	234.10
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	**9.64**	25.21	35.01	34.04	35.58	36.49	37.46	36.59	33.99	33.94	33.00	34.85	59.48	142.29	251.72
	(0.98)	(0.98)	(1.02)	(1.00)	(1.00)	(1.01)	(1.02)	(1.03)	(1.01)	(1.01)	(1.00)	(1.04)	(0.96)	(1.00)	(1.08)
OLS plus USDRE	9.74	25.64	34.74	34.16	35.59	36.20	36.93	35.91	33.79	33.64	32.58	34.46	59.50	141.56	228.40
	(0.99)	(1.00)	(1.01)	(1.00)	(1.00)	(1.00)	(1.01)	(1.01)	(1.01)	(1.00)	(0.99)	(1.03)	(0.96)	(0.99)	(0.98)
Adaptive LASSO	10.04	**23.94***	34.48	34.02	34.63	35.75	35.89	36.40	34.19	33.67	33.35	36.25	**59.45**	141.48	227.40
	(1.02)	(0.93)	(1.00)	(1.00)	(0.98)	(0.99)	(0.98)	(1.03)	(1.02)	(1.00)	(1.01)	(1.08)	(0.96)	(0.99)	(0.97)
Adaptive LASSO plus USDRE	10.04	24.04*	34.48	33.65	35.61	36.77	35.68	36.33	34.84	33.79	32.68	36.25	59.47	143.36	228.34
	(1.02)	(0.94)	(1.00)	(0.99)	(1.00)	(1.02)	(0.97)	(1.03)	(1.04)	(1.01)	(0.99)	(1.08)	(0.96)	(1.00)	(0.98)
Random Forest	17.97	27.13	34.18	32.25	33.14*	**34.13***	**33.76****	**33.52**	**32.29**	**32.11**	32.08	33.76	66.39	141.22	**210.25**
	(1.83)	(1.06)	(0.99)	(0.95)	(0.93)	(0.94)	(0.92)	(0.95)	(0.96)	(0.96)	(0.97)	(1.01)	(1.07)	(0.99)	(0.90)
Random Forest plus USDRE	18.05	27.29	**33.60**	**31.97**	**32.85***	34.83	34.01	34.10	32.64	33.01	**31.97**	33.84	65.49	**137.95**	222.23
	(1.84)	(1.06)	(0.98)	(0.94)	(0.93)	(0.96)	(0.93)	(0.96)	(0.97)	(0.98)	(0.97)	(1.01)	(1.06)	(0.97)	(0.95)

Notes: Table presents MAE for forecasts covering months when FOCUS standard deviations of long-term inflation forecasts was above the sample period median. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest MAE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

Table 1.11: Pseudo out-of-Sample RMSE for inflation forecasts - low FOCUS uncertainty

	Inflation h months ahead - RMSE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	9.87	25.04	**30.93**	**33.26**	**32.46**	33.20	36.67	38.65	41.30	40.35	40.84	37.86	**47.63**	**85.79**	187.87
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	**9.35****	**24.96**	31.67	34.02	33.02	33.43	36.46	38.29	41.18	40.11	**40.63**	**37.47**	48.85	86.69	176.37
	(0.95)	(1.00)	(1.02)	(1.02)	(1.02)	(1.01)	(0.99)	(0.99)	(1.00)	(0.99)	(0.99)	(0.99)	(1.03)	(1.01)	(0.94)
OLS plus USDRE	9.35*	25.12	31.46	33.75	32.83	32.99	35.92	37.48*	40.31	**39.88**	41.11	37.78	48.92	86.88	**174.49**
	(0.95)	(1.00)	(1.02)	(1.01)	(1.01)	(0.99)	(0.98)	(0.97)	(0.98)	(0.99)	(1.01)	(1.00)	(1.03)	(1.01)	(0.93)
Adaptive LASSO	9.97	25.73	31.35	34.72	34.16	33.14	36.97	37.68	41.06	41.16	42.24	38.81	49.42	90.55	181.59
	(1.01)	(1.03)	(1.01)	(1.04)	(1.05)	(1.00)	(1.01)	(0.97)	(0.99)	(1.02)	(1.03)	(1.03)	(1.04)	(1.06)	(0.97)
Adaptive LASSO plus USDRE	9.97	25.46	31.55	34.64	33.56	33.31	36.53	37.57	40.69	41.23	42.16	38.81	49.33	89.51	177.36
	(1.01)	(1.02)	(1.02)	(1.04)	(1.03)	(1.00)	(1.00)	(0.97)	(0.99)	(1.02)	(1.03)	(1.03)	(1.04)	(1.04)	(0.94)
Random Forest	17.03	29.29	33.68	37.85	35.98	33.63	36.67	36.85	**38.85**	40.19	42.45	39.87	57.60	106.17	185.84
	(1.73)	(1.17)	(1.09)	(1.14)	(1.11)	(1.01)	(1.00)	(0.95)	(0.94)	(1.00)	(1.04)	(1.05)	(1.21)	(1.24)	(0.99)
Random Forest plus USDRE	17.05	29.01	33.14	36.25	34.70	**32.18**	**35.65**	**36.40**	39.06	40.17	42.41	39.56	56.70	98.51	174.76
	(1.73)	(1.16)	(1.07)	(1.09)	(1.07)	(0.97)	(0.97)	(0.94)	(0.95)	(1.00)	(1.04)	(1.04)	(1.19)	(1.15)	(0.93)

Notes: Table presents RMSE for forecasts covering months when FOCUS standard deviations of long-term inflation forecasts was below the sample period median. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest RMSE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

Table 1.12: Pseudo out-of-Sample MAE for inflation forecasts - low FOCUS uncertainty

	Inflation h months ahead - MAE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	8.41	18.19	**22.22**	**24.62**	**23.76**	24.52	27.40	29.10	31.82	31.24	32.05	29.52	**39.18**	69.88	113.31
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	8.00*	18.08	23.78	26.29	25.15	25.36	27.38	28.66	31.65	**31.08**	**32.03**	**28.62**	40.97	**68.12**	108.07
	(0.95)	(0.99)	(1.07)	(1.07)	(1.06)	(1.03)	(1.00)	(0.98)	(0.99)	(1.00)	(1.00)	(0.97)	(1.05)	(0.97)	(0.95)
OLS plus USDRE	**8.00***	**17.94**	22.88	25.19	24.25	24.49	26.65	28.29	31.25	31.09	32.47	28.84	40.05	69.45	**107.53**
	(0.95)	(0.99)	(1.03)	(1.02)	(1.02)	(1.00)	(0.97)	(0.97)	(0.98)	(1.00)	(1.01)	(0.98)	(1.02)	(0.99)	(0.95)
Adaptive LASSO	8.54	19.79	24.34	27.30	26.57	25.53	27.68	28.27	32.14	32.48	34.08	29.99	41.15	70.16	135.33
	(1.01)	(1.09)	(1.10)	(1.11)	(1.12)	(1.04)	(1.01)	(0.97)	(1.01)	(1.04)	(1.06)	(1.02)	(1.05)	(1.00)	(1.19)
Adaptive LASSO plus USDRE	8.54	19.63	23.99	27.19	25.97	25.54	27.51	28.25	31.82	32.32	33.93	29.99	40.56	71.40	129.33
	(1.01)	(1.08)	(1.08)	(1.10)	(1.09)	(1.04)	(1.00)	(0.97)	(1.00)	(1.03)	(1.06)	(1.02)	(1.04)	(1.02)	(1.14)
Random Forest	13.41	23.04	26.04	29.48	27.78	25.85	27.47	27.86	**29.88**	31.19	33.50	31.62	49.58	81.58	136.46
	(1.59)	(1.27)	(1.17)	(1.20)	(1.17)	(1.05)	(1.00)	(0.96)	(0.94)	(1.00)	(1.05)	(1.07)	(1.27)	(1.17)	(1.20)
Random Forest plus USDRE	13.37	22.58	25.38	27.53	26.34	**24.34**	**26.46**	**27.53**	29.96	31.30	33.56	31.01	48.70	77.64	128.06
	(1.59)	(1.24)	(1.14)	(1.12)	(1.11)	(0.99)	(0.97)	(0.95)	(0.94)	(1.00)	(1.05)	(1.05)	(1.24)	(1.11)	(1.13)

Notes: Table presents MAE for forecasts covering months when FOCUS standard deviations of long-term inflation forecasts was below the sample period median. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest MAE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

During high-uncertainty periods, inflation becomes substantially more "forecastable" by all methods. For cumulative 12-month inflation, every competing forecasting procedure achieves lower RMSE and MAE compared to FOCUS. Random Forest attains a 13% improvement over FOCUS in terms of RMSE, while Adaptive LASSO achieves 12% gain. Similarly, at the 6-month cumulative horizon, all alternative methods also outperform FOCUS. This finding is noteworthy in itself and aligns with the theoretical prediction of Cujean & Hasler (2017) that asset prices (or macroeconomic variables in our case) become more predictable during periods of elevated disagreement among market participants.

However, the incremental gain from incorporating USDRE appears more limited during high-uncertainty episodes. Comparing USDRE-augmented forecasts to their non-HFRE counterparts, the improvements are modest or absent. For instance, Random Forest plus USDRE achieves a higher cumulative 12-month RMSE than Random Forest without USDRE. Similarly with the Adaptive LASSO forecasts. This pattern suggests that USDRE itself may become noisier during high-uncertainty periods, as disagreement among hedge fund managers likely correlates with disagreement among professional forecasters more broadly.

This pattern reverses during low-uncertainty periods, reported in Tables 1.11 and 1.12. Here, forecasting procedures incorporating USDRE systematically outperform their counterparts without HFRE data, particularly for longer-term inflation. For cumulative 12-month forecasts, Random Forest plus USDRE achieves a striking 6% reduction in RMSE relative to Random Forest while Adaptive LASSO plus USDRE achieves a 3% reduction relative to Adaptive LASSO.

This state-dependent performance teases out a nuanced relationship between hedge fund positioning and forecast accuracy. When professional forecasters exhibit consensus views and uncertainty is low, hedge fund USD exposures appear to provide a valuable incremental signal that enhances prediction. Conversely, during turbulent periods when all forecasters struggle with elevated uncertainty, the relative advantage of incorporating USDRE diminishes as the signal-to-noise ratio in positioning data may deteriorate alongside broader informational challenges. Nevertheless, the absolute forecast performance of all methods improves during high uncertainty, suggesting that heightened disagreement paradoxically coincides with greater ex-post predictability of inflation outcomes.

1.5.5 Discussion of Results

The observed relationship between hedge fund USD exposure and future inflation admits multiple interpretations. One possibility is active timing: hedge funds may have enhanced information-processing capabilities, enabling them to anticipate inflationary pressures and adjust currency positions accordingly. Under this interpretation, their positioning reflects forward-looking views that subsequently materialize in realized inflation. Alternatively, the relationship could reflect defensive positioning: hedge funds may increase USD exposure not to profit from expected inflation but to hedge against currency depreciation that typically accompanies inflationary episodes in emerging markets. A third possibility involves self-fulfilling dynamics: if large hedge fund flows into USD futures affect exchange rates, and exchange rate movements feed through to inflation via import prices, then hedge fund positioning could partially cause the inflation it appears to predict. Our reduced-form analysis cannot definitively distinguish among these mechanisms. Nevertheless, the robust predictive power of hedge fund positioning suggests that monitoring these exposures provides valuable information for forecasters and policymakers, regardless of the underlying causal channel.

1.6 Conclusion

This essay investigates whether macro hedge fund risk exposures contain predictive information about future inflation. Using daily data on 438 Brazilian macro hedge funds from January 2006 to August 2024, we estimate time-varying exposures to seven macro-sensitive risk factors via a Kalman filter procedure and optimal changepoint regression methods. The central empirical finding is that hedge fund exposure to the BRL/USD exchange rate significantly predicts cumulative 12-month inflation.

Incorporating this hedge fund risk exposure (HFRE) data into forecasting models yields statistically and economically meaningful improvements in out-of-sample forecast accuracy. OLS plus USDRE achieves the lowest mean absolute error for cumulative 12-month inflation forecasts, reducing MAE by 3% relative to the FOCUS benchmark.

These results make three contributions to the literature. First, they introduce hedge fund risk exposure data as a novel predictor in inflation forecasting, demonstrating that sophisticated investors' positioning conveys forward-looking information about macroeconomic conditions. Second, they show that high-dimensional forecasting models perform disproportionately better than

survey forecasts specifically during periods of elevated inflation uncertainty, when forecasting is most challenging. Third, they provide empirical support for theories of hedge fund market-timing ability, showing that funds' dynamic positioning predicts macroeconomic outcomes beyond simply responding to them.

1.A Results Assuming State-Space Model

This appendix presents robustness checks for the main inflation forecasting results using hedge fund risk exposures estimated assuming a state-space model with stochastic state variables rather than a structural break model. As described in Section 1.3 of Chapter 1, the state-space model with time-varying betas as latent variables allows for smooth evolution of risk exposures over time.

Table 1.A.13 replicates the in-sample regression analysis from Table 6 in Chapter 1, replacing exposures estimated through a optimal changepoint procedure with estimates derived from a Kalman filter approach. The pattern of coefficients is consistent with the main results. USDRE exhibits increasing predictive power at longer horizons, achieving statistical significance at both the 9-month horizon (coefficient = 0.10, t-statistic = 2.05) and the 12-month horizon (coefficient = 0.15, t-statistic = 2.20). These results are marginally stronger than those obtained using changepoint estimates, where USDRE significance emerges primarily at the 12-month horizon. The consistent finding that USDRE predicts longer-term inflation across both estimation methods reinforces the robustness of this relationship.

Tables 1.A.14 and 1.A.15 present out-of-sample forecast evaluation using Kalman filter-based USDRE. The results closely parallel those in Chapter 1.

Table 1.A.13: Regression of cumulative inflation on FOCUS forecasts and macro hedge fund risk exposure data (estimated via Kalman filter)

Variable	3M	6M	9M	12M
Intercept	**-0.00**	-0.00	0.01	**0.03**
	(-2.57)	(-0.72)	(0.57)	**(2.15)**
FOCUS Forecast	**1.29**	**1.16**	0.75	0.35
	(15.62)	**(5.90)**	(1.79)	(1.16)
BXMKTRE	**0.04**	0.09	0.11	0.16
	(2.21)	(1.31)	(0.83)	(1.03)
BXBOND1YRE	-0.00	-0.00	-0.01	-0.01
	(-0.62)	(-0.92)	(-0.88)	(-0.45)
BXBOND5YRE	-0.01	-0.02	-0.03	-0.06
	(-0.93)	(-0.85)	(-0.92)	(-1.32)
BXINF5YRE	-0.01	0.03	0.08	0.05
	(-0.33)	(0.35)	(0.56)	(0.34)
USDRE	0.00	0.04	**0.10**	**0.15**
	(0.47)	(1.31)	**(2.05)**	**(2.20)**
R^2	0.71	0.53	0.42	0.42
Observations	224	224	224	224

Note: This table presents estimated coefficients from linear regressions in which the dependent variable are the cumulative inflation over selected horizons - 3, 6, 9 and 12 months ahead - and the independent variables are the FOCUS forecast for the appropriate horizon and the macro hedge fund estimated risk exposures to BXMKT, BXBOND1Y, BXBOND5Y, BXINF5Y and USD. Newey-West adjusted t-statistics are presented between parentheses. Bold indicates |t-stat| $>$ 1.96.

Table 1.A.14: Pseudo out-of-Sample RMSE for inflation forecasts incorporating macro hedge fund risk exposure data (estimated via Kalman filter)

	Inflation h months ahead - RMSE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	12.13	30.75	39.80	40.83	41.14	41.63	43.18	43.51	43.69	43.70	43.91	42.60	66.01	139.59	273.77
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	11.34**	**29.61****	40.02	40.84	**41.05**	41.53	42.92	43.25	43.42	43.38	43.56	42.40	**63.59***	**136.22**	262.10
	(0.93)	(0.96)	(1.01)	(1.00)	(1.00)	(1.00)	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(1.00)	(0.96)	(0.98)	(0.96)
OLS plus USDRE	**11.27****	29.69*	40.16	40.92	41.05	41.36	42.47**	42.79*	43.17	43.19	**43.25**	**42.21**	63.69*	136.68	258.45*
	(0.93)	(0.97)	(1.01)	(1.00)	(1.00)	(0.99)	(0.98)	(0.98)	(0.99)	(0.99)	(0.98)	(0.99)	(0.96)	(0.98)	(0.94)
Adaptive LASSO	12.12	30.01	**39.34**	41.09	41.58	41.37	42.07	42.74	43.41	43.46	43.63	42.93	64.76	137.02	245.93
	(1.00)	(0.98)	(0.99)	(1.01)	(1.01)	(0.99)	(0.97)	(0.98)	(0.99)	(0.99)	(0.99)	(1.01)	(0.98)	(0.98)	(0.90)
Adaptive LASSO plus USDRE	12.12	30.05	39.64	**40.50**	41.58	41.43	42.08	42.79	43.67	43.02	43.34	42.93	64.98	136.69	**244.41***
	(1.00)	(0.98)	(1.00)	(0.99)	(1.01)	(1.00)	(0.97)	(0.98)	(1.00)	(0.98)	(0.99)	(1.01)	(0.98)	(0.98)	(0.89)
Random Forest	21.64	33.60	40.77	41.89	41.71	41.40	**41.55**	41.44	**42.11**	**42.79**	44.26	43.66	74.63	144.37	245.41
	(1.78)	(1.09)	(1.02)	(1.03)	(1.01)	(0.99)	(0.96)	(0.95)	(0.96)	(0.98)	(1.01)	(1.02)	(1.13)	(1.03)	(0.90)
Random Forest plus USDRE	21.64	33.31	40.42	41.51	41.50	**41.30**	41.68	**41.43**	42.43	42.87	44.41	43.67	73.85	143.25	244.53*
	(1.78)	(1.08)	(1.02)	(1.02)	(1.01)	(0.99)	(0.97)	(0.95)	(0.97)	(0.98)	(1.01)	(1.03)	(1.12)	(1.03)	(0.89)

Notes: Total of 97 ($h = 1$) to 86 ($h = 12$) forecasts covering the period between August 2016 and August 2024. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest RMSE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

Table 1.A.15: Pseudo out-of-Sample MAE for inflation forecasts incorporating macro hedge fund risk exposure data (estimated via Kalman filter)

	Inflation h months ahead - MAE (x10,000)												Cumulative		
Model	1	2	3	4	5	6	7	8	9	10	11	12	3M	6M	12M
FOCUS	9.12	21.90	**28.30**	**29.39**	**29.74**	30.53	32.23	32.43	32.73	32.49	32.56	**31.63**	50.57	107.52	177.26
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
FOCUS with bias correction	8.82	**21.61**	29.40	30.21	30.48	31.11	32.65	32.85	32.90	32.63	**32.55**	31.92	50.22	**106.43**	184.12
	(0.97)	(0.99)	(1.04)	(1.03)	(1.02)	(1.02)	(1.01)	(1.01)	(1.01)	(1.00)	(1.00)	(1.01)	(0.99)	(0.99)	(1.04)
OLS plus USDRE	**8.82**	21.80	29.02	29.71	30.19	30.79	32.02	32.22	32.71	32.56	32.61	31.82	**49.97**	106.63	173.22
	(0.97)	(1.00)	(1.03)	(1.01)	(1.02)	(1.01)	(0.99)	(0.99)	(1.00)	(1.00)	(1.00)	(1.01)	(0.99)	(0.99)	(0.98)
Adaptive LASSO	9.29	21.84	29.41	30.70	30.69	30.81	31.97	32.56	33.24	33.12	33.69	33.30	50.30	107.00	184.07
	(1.02)	(1.00)	(1.04)	(1.04)	(1.03)	(1.01)	(0.99)	(1.00)	(1.02)	(1.02)	(1.03)	(1.05)	(0.99)	(1.00)	(1.04)
Adaptive LASSO plus USDRE	9.29	21.87	29.44	30.27	30.83	31.12	32.07	32.79	33.53	32.90	33.41	33.30	50.41	107.83	183.54
	(1.02)	(1.00)	(1.04)	(1.03)	(1.04)	(1.02)	(1.00)	(1.01)	(1.02)	(1.01)	(1.03)	(1.05)	(1.00)	(1.00)	(1.04)
Random Forest	15.75	25.00	30.21	30.60	30.29	30.27	30.63*	30.83	31.01	**31.76**	32.96	32.77	58.15	112.05	175.47
	(1.73)	(1.14)	(1.07)	(1.04)	(1.02)	(0.99)	(0.95)	(0.95)	(0.95)	(0.98)	(1.01)	(1.04)	(1.15)	(1.04)	(0.99)
Random Forest plus USDRE	15.68	24.74	29.67	30.22	29.88	**29.77**	**30.53***	**30.59**	**30.97**	31.86	33.05	32.60	57.08	110.13	**171.30**
	(1.72)	(1.13)	(1.05)	(1.03)	(1.00)	(0.97)	(0.95)	(0.94)	(0.95)	(0.98)	(1.02)	(1.03)	(1.13)	(1.02)	(0.97)

Notes: Total of 97 ($h = 1$) to 86 ($h = 12$) forecasts covering the period between August 2016 and August 2024. ***, **, and * indicate that, for a specific horizon, model performed statistically better than the FOCUS forecast at 1%, 5% and 10% significance levels in a one-tailed Diebold-Mariano test. The values highlighted in bold indicate the model with lowest MAE at each horizon. Forecasts for the cumulative 3, 6 and 12 months are computed by adding the individual monthly forecasts.

1.B
Inflation Predictors in High-dimension

Following the macroeconomic forecasting literature (Garcia *et al.*, 2017; Medeiros *et al.*, 2021), we consider a large set of inflation predictors, including both contemporaneous values and lags. Our dataset comprises 64 macroeconomic variables covering price indices, monetary aggregates, commodity prices, economic activity, employment, financial and market variables, credit conditions, government debt, exchange rates, and international transactions. Table 1.B.16 provides the complete list of predictive variables used in the baseline adaptive LASSO and random forest inflation forecasting models, along with their descriptions, units, number of lags, and timing of availability.

Table 1.B.16: Description of predictive variables

#	Variable	Description	Unit	Lags	Last available
		Price Indexes			
1	IPCA	Broad Consumer Price Index	% change per month	5	t-1
2	FOCUS-IPCA	FOCUS inflation expectation	% change per month	0	t
3	INPC	National Consumer Price Index	% change per month	1	t-1
4	IPCA15	IPCA-15 Preliminary Inflation Index	% change per month	1	t
5	IPC-Br	IPC-Br Index	% per month	1	t-1
6	IPC-M	IPC-M Index	% change per month	1	t-1
7	IGP-M	General Market Price Index	% change per month	1	t-1
8	IGP-DI	General Price Index - Domestic Supply	% change per month	1	t-1
9	IGP-10	IGP-10 Index	% per month	1	t-1
10	IPC-Fipe	IPC-Fipe Index	% change per month	1	t-1
11	IPA	Producer Price Index - Wholesale	% change per month	1	t-1
12	IPA-Ind	IPA Industrial Index	% per month	1	t-1
13	IPA-Agr	IPA Agricultural Index	% per month	1	t-1
14	INCC	National Index of Construction Costs	% change per month	1	t-1
15	INCC-R	National Index of Construction Costs - Residential	% change per month	1	t-1
		Monetary Aggregates			
16	BM	Monetary Base - monthly average balance	% change per month	2	t-2
17	BMB	Broad Monetary Base - end of period balance	% change per month	2	t-2
18	M1	Money Supply M1 - end of period balance	% change per month	2	t-2
19	M2	Money Supply M2 - end of period balance	% change per month	2	t-2
20	M3	Money Supply M3 - end of period balance	% change per month	2	t-2
21	M4	Money Supply M4 - end of period balance	% change per month	2	t-2
		Commodities Prices			
22	ICBR	Brazilian Commodity Index (All)	% change per month	2	t-1
		Economic Activity			
23	IBC-Br	Brazilian Economic Activity Index	% change per month	2	t-3
24	Month-GDP	Monthly GDP	% real change per month	1	t-2
25	TCU	Total Capacity Utilization	first difference	1	t-1
26	PIMPF	Industrial Production Index	% change per month	1	t-2
27	PMC-Total	Retail Sales Volume - Total	% change per month	1	t-2
28	PMC-Fuel	Retail Sales Volume - Fuels	% change per month	1	t-2
29	PMC-Supermarket	Retail Sales Volume - Supermarkets	% change per month	1	t-2
30	PMC-Clothing	Retail Sales Volume - Clothing	% change per month	1	t-2
31	Elec	Total Electricity Consumption	% change per month	2	t-2
		Employment			
32	Unem	Unemployment Rate	first difference	1	t-2
33	Employment	Registered Employment	first difference	1	t-1
34	Aggreg-Wage	Broad Wage Income	first difference	1	t-1
35	Min-Wage	Minimum Wage	first difference	0	t
36	Income	Household Disposable Income	first difference	1	t-2

Notes: "Lags" column indicates number of additional lags included in the model. "Last available" indicates the last available observation when forecasts are being computed.

Table 1.B.16: Description of Predictive Variables (cont.)

#	Variable	Description	Unit	Lags	Last available
		Financial and Market Variables			
37	Ibovespa	Ibovespa Index	% change per month	1	t
38	IRF-M	Anbima Market Index (Pre-fixed Bonds)	% change per month	1	t
39	IMA-S	Anbima Market Index (Selic Bonds)	% change per month	1	t
40	IMA-B	Anbima Market Index (IPCA Bonds)	% change per month	1	t
41	IMA	General Anbima Market Index	% change per month	1	t
42	Saving Deposits	Savings Deposits Balance	% change per month	1	t
43	Selic	Selic Basic Interest Rate	first difference	1	t
44	CDI	Cetip Interbank Deposit Rate	% change per month	1	t
45	TJLP	Long-term Interest Rate	% first difference	1	t
46	EMBI	Emerging Markets Bond Index - Brazil	first difference	1	t
47	VIX	CBOE Volatility Index	first difference	1	t
		Credit and Government Debt			
48	Cred-Total	Total Credit Outstanding	% change per month	1	t-2
49	Cred-GDP	Credit as % of GDP	first difference	1	t-2
50	Indebt-House1	Household Debt to Income	% first difference	1	t-2
51	Indebt-House2	Household Debt (Excl. Mortgage)	% first difference	1	t-2
52	Net-Gov-Debt	Net Government Debt as % of GDP	first difference	1	t-2
53	Net-Debt-States	Net Debt of State Governments as % of GDP	first difference	1	t-2
54	Net-Debt-Municipalities	Net Debt of Municipal Governments as % of GDP	first difference	1	t-2
55	Gross-Gov-Debt	Gross Government Debt as % of GDP	first difference	1	t-2
56	Primary-Gov-Result	Primary Government Result as % of GDP	level	1	t-2
57	Duration-Public-Debt	Duration of Public Debt	level	1	t-2
		Exchange Rates and International Transactions			
58	REER	Real Effective Exchange Rate	% change per month	1	t
59	BRL/USD	BRL/USD Exchange Rate	% change per month	2	t
60	BRL/EUR	BRL/EUR Exchange Rate	% change per month	1	t
61	Current-Account	Current Account Balance	% change per month	1	t-2
62	Trade-Balance	Trade Balance	% change per month	1	t-2
63	Exports	Exports	% change per month	1	t-2
64	Imports	Imports	% change per month	1	t-2

Notes: "Lags" column indicates number of additional lags included in the model. "Last available" indicates the last available observation when forecasts are being computed.

1.B.1 Adaptive LASSO

The adaptive LASSO (Zou, 2006) is a regularized regression method designed to perform variable selection and parameter estimation simultaneously in high-dimensional settings.

The standard LASSO estimator solves the following penalized least squares problem:

$$\hat{\beta}^{LASSO} = \arg\min_{\beta} \left\{ \sum_{t=1}^{T} (y_t - \mathbf{x}_t'\beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}, \tag{1.B.11}$$

where y_t denotes the target variable (inflation), $\mathbf{x}_t$ is a p-dimensional vector of predictors, β is the coefficient vector, and $\lambda \geq 0$ is a tuning parameter that controls the degree of penalization. The L1 penalty induces sparsity, setting some coefficients exactly to zero and thus performing variable selection.

The adaptive LASSO extends this framework by applying data-driven penalty weights to different coefficients:

$$\hat{\beta}^{ALASSO} = \arg\min_{\beta} \left\{ \sum_{t=1}^{T} (y_t - \mathbf{x}_t'\beta)^2 + \lambda \sum_{j=1}^{p} w_j |\beta_j| \right\}, \tag{1.B.12}$$

where $w_j = |\tilde{\beta}_j|^{-\gamma}$ are adaptive weights constructed from an initial consistent estimator $\tilde{\beta}$ (in our case via a standard LASSO), and $\gamma > 0$ is a power parameter (which we set to 1 as standard). This adaptive weighting scheme allows the penalty to depend on the magnitude of initial estimates, yielding improved properties: the adaptive LASSO consistently selects the correct subset of nonzero coefficients and estimates them with the same asymptotic efficiency as if the true model were known in advance.

1.B.2 Random Forest

Random forest (Breiman, 2001) is an ensemble learning method that aggregates predictions from multiple decision trees to produce robust forecasts. The algorithm constructs a collection of decision trees, each trained on a bootstrap sample of the data and using a random subset of predictors at each node split. This combination of bagging (bootstrap aggregating) and random feature selection reduces overfitting and improves out-of-sample performance relative to individual trees.

For a regression problem with target variable y_t and predictors $\mathbf{x}_t$, the random forest forecast is computed as:

$$\hat{y}_t = \frac{1}{B} \sum_{b=1}^{B} T_b(\mathbf{x}_t), \tag{1.B.13}$$

where B is the number of trees in the forest and $T_b(\mathbf{x}_t)$ denotes the prediction from the b-th tree. Each tree T_b is grown on a bootstrap sample of the training data, and at each node split, only a random subset of m predictors (out of p total) is considered. The typical choice is $m \approx p/3$ for regression problems.

Random forests exhibit several desirable properties for macroeconomic forecasting: they handle nonlinear relationships and interactions among predictors automatically, are robust to outliers and irrelevant variables, and provide implicit variable importance measures. Medeiros *et al.* (2021) demonstrate that random forests perform competitively with other machine learning methods for Brazilian inflation forecasting.

In our application, we implement random forests using the following hyperparameters: 1000 trees, $m = p/3$ predictors considered at each split, and minimum node size of 3 observations.

2
Conditioning Hedge Fund Replication Strategies on Cross-sectional Dispersion: the Case of Brazilian Macro Hedge Funds

Abstract. This essay investigates whether the performance of hedge fund replication strategies can be improved by conditioning on the cross-sectional dispersion in estimated risk exposures across funds. Using daily data on 438 Brazilian macro hedge funds from January 2006 to August 2024, we estimate time-varying exposures and construct replication strategies that scale positions based on cross-sectional estimated exposure dispersion. The central finding is that conditioning on dispersion enhances performance: a replication strategy that scales exposures inversely with dispersion achieves an annualized 4-factor alpha of 5.09% (t-statistic = 1.96), compared to 2.22% (t-statistic = 1.21) for the unconditional strategy. When controlling for a sensible multi-factor time-series momentum strategy across the same set of risk factors, the dispersion-conditional still strategy generates an alpha of 4.02% (t-statistic = 1.72) with substantially lower maximum drawdown (-16.96% vs. -21.24%). These results suggest that cross-sectional dispersion in hedge fund positioning is an informative signal that can be exploited in the construction of trading strategies.

Keywords: hedge fund replication; time-series momentum; risk exposures; dispersion; trading strategies; multifactor strategies

2.1 Introduction

Hedge fund replication strategies aim to construct portfolios using liquid instruments to mimic hedge fund returns at lower cost (Hasanhodzic & Lo, 2007; Fung & Hsieh, 2008). This essay investigates whether cross-sectional dispersion in estimated hedge fund exposures can improve such replication strategies. Low dispersion may indicate a higher degree of consensus among hedge funds, potentially reflecting stronger private information on future asset prices. Conversely, high dispersion may be a signal of disagreement and low conviction. we test whether conditioning replication strategies on this dispersion measure enhances performance relative to unconditional approaches.

The investigation of cross-sectional dispersion as a conditioning signal is also motivated by research linking disagreement to business cycle dynamics. Cujean & Hasler (2017) propose a model in which time-series momentum (ts-mom) strategies, which take long positions in assets with positive past returns and short positions in assets with negative past returns, exhibit stronger performance in bad states when overall disagreement is larger. However, the literature on this relationship remains mixed: Hutchinson & O'Brien (2020) document that ts-mom strategies are more profitable in good states and expansions. In any case, these insights suggest that cross-sectional dispersion in hedge fund exposures may be related to overall disagreement and could provide informative signals relevant for systematic trading strategies. Two hypotheses merit further investigation: first, low dispersion may reflect genuine information or strong conviction among sophisticated investors; second, dispersion itself may proxy for measurement uncertainty in aggregate exposures, with low dispersion indicating more precise signals.

The Brazilian context provides a natural laboratory for this investigation. Daily reporting requirements yield high-frequency data on fund returns, eliminating survivorship bias and enabling more precise estimation of time-varying exposures. Brazilian macro hedge funds often trade several liquid assets such as government bonds and futures contracts on equity indices, interest rates and exchange rates, making replication strategies implementable with modest transaction costs.

Using the same sample of 438 macro hedge funds described in Chapter 1, we construct replication strategies based on lagged aggregate exposures estimated via optimal changepoint regression. A simple unconditional replication strategy yields modest performance. The key innovation is to condition these strategies on cross-sectional dispersion in exposures, implementing both binary and continuous scaling approaches. we construct Brazilian time-series

momentum strategies as a benchmark, following Moskowitz *et al.* (2012) and Hurst *et al.* (2017), to assess whether hedge fund alpha reflects true alpha after controlling for ts-mom exposure. Similar to Moreira & Muir (2017), we scale positions in multi-factor portfolios - though in our case, scaling is based on cross-sectional dispersion rather than volatility.

Main Results. We report three main findings. First, an aggregate macro hedge fund portfolio exhibits strong alpha: the NAV-weighted portfolio generates an annualized 4-factor alpha of 3.18% with a t-statistic of 4.75, statistically significant at the 1% level. This indicates that actual hedge fund returns significantly exceed what can be explained by passive exposures to Brazilian and US equity and bond markets. The equal-weighted portfolio shows a more modest alpha of 1.03% with a t-statistic of 1.85, statistically significant at the 10% level.

An important question is whether hedge fund performance simply reflects exposure to time-series momentum, given the well documented importance of trend-following strategies in explaining hedge fund returns. To investigate this, we extend the performance attribution by regressing hedge fund returns on both the four-factor model and a diversified time-series momentum strategy that we construct. The NAV-weighted aggregate hedge fund portfolio generates a positive alpha with t-statistic of 4.04 after controlling for both the four-factor model and time-series momentum. This indicates that Brazilian macro hedge funds, as a class, deliver returns beyond simple trend-following. These results suggest that hedge funds employ sophisticated strategies that go beyond mechanical momentum signals and confirm the potential value of replication strategies.

Second, a simple replication strategy based on lagged aggregate exposures captures only a fraction of this performance. The replication intuition is simple: for any of the five risk factors defined in Chapter directly constructed from asset prices - BXMKT, USD, BXOBD1Y, BXOND5Y and BXINF5Y - the strategy takes a position (either long or short) equal to the estimated aggregate risk exposure to that factor in the previous month. Not accounting for rollover and trading costs, this strategy achieves an annualized 4-factor alpha of 0.49% with a t-statistic of 1.21 - not significant at conventional levels. After controlling for our time-series momentum strategy, the t-statistic of the estimated alpha falls to 0.62.

Third, conditioning the replication strategy on exposure dispersion improves performance substantially. We define dispersion for each risk factor as the cross-sectional standard deviation of estimated exposures across funds. Low

dispersion indicates alignment in positioning and potentially higher conviction. We implement replication strategies that condition on dispersion in two ways. The first one only replicates the exposure to a given factor if dispersions associated with that factor is below its 36-month median. The second one scales positions inversely with dispersion - with the scaling factor approaching 1 (0) when dispersion is close to its 36-month minimum (maximum). These strategies achieve annualized 4-factor alpha of 0.54% with t-statistic of 1.83 (binary conditioning) and of 0.34% with t-statistic of 1.96 (scaling factor) - significant at a 10% level. After controlling for time-series momentum, the t-statistic of the estimated alphas are 1.71 (binary conditioning) and 1.72 (scaling factor). Importantly, maximum drawdowns decrease substantially: scaling both strategies to the same ex-post annualized volatility, the scaling factor strategy exhibits a -16.96% maximum drawdown over the sample period versus -21.24% for the simple replication strategy.

The ability of the dispersion-conditional replication strategies to generate meaningful alpha suggests that cross-sectional factor exposure dispersion may contain genuine information about future factor returns.

Practical Implementation. The dispersion-conditional replication strategies presented here are highly implementable. They require positions in only five liquid Brazilian instruments (equity index future, exchange rate future, interest rate future and inflation-linked government bonds), with monthly rebalancing sufficient to capture hedge fund positioning. Transaction costs in these markets are modest and the underlying assets exhibit substantial liquidity. Nevertheless, capacity constraints and transaction cost analysis merit further investigation, as do the strategies' performance during periods of extreme market stress when liquidity may temporarily deteriorate. These practical considerations remain subjects for future research and real-world implementation.

Contribution. This essay contributes to the hedge fund replication literature by incorporating cross-sectional dispersion in exposures as a conditioning signal. Prior work on hedge fund replication focuses on matching aggregate returns through factor exposures (Hasanhodzic & Lo, 2007; Fung & Hsieh, 2008) or constructing portfolios of liquid securities with similar characteristics (Kat & Palaro, 2007). Recent studies estimate dynamic exposures using rolling windows (O'Doherty *et al.*, 2017; Duanmu *et al.*, 2020), state-space models (Lambert & Platania, 2020), or regime-switching frameworks (Billio *et al.*, 2012). However, these approaches do not exploit cross-sectional information about dispersion in positioning.

The finding that low-dispersion periods yield stronger predictability connects to theoretical work on information aggregation in financial markets. Cujean & Hasler (2017) develop a model in which momentum strategies are more profitable during periods of higher uncertainty, as informed traders' positioning becomes more informative. In our context, low dispersion may signal periods when hedge funds possess higher-quality information or greater conviction, making their aggregate positioning a more reliable signal.

This essay also extends the time-series momentum literature by demonstrating the profitability of these strategies in Brazilian markets. Moskowitz *et al.* (2012) document momentum across diverse asset classes using US and global data, while Hurst *et al.* (2017) examine trend-following strategies in managed futures. Our results confirm that similar patterns exist in Brazilian equity, currency, and fixed income futures markets. As noted by Kim *et al.* (2016), volatility scaling plays an important role in momentum strategy performance, a feature we incorporate in all multi-factor time-series momentum strategy implementations.

Finally, the essay contributes to understanding cross-sectional variation in hedge fund behavior. Racicot & Théoret (2016) find that dispersion in hedge fund market betas declines during periods of macroeconomic uncertainty, while Gregoriou *et al.* (2021) show that dispersion in higher moment exposures responds to macroeconomic shocks. Our evidence suggests that dispersion itself contains valuable information for strategy construction.

Essay Overview. The remainder of this essay proceeds as follows. Section 2.2 reviews the literature on time-series momentum strategies and hedge fund replication. Section 2.3 briefly summarizes the data, which is identical to Chapter 1. Section 2.4 documents time-series momentum patterns in Brazilian risk factors. Section 2.5 presents the simple hedge fund replication strategy and results. Section 2.6 introduces dispersion-conditional replication strategies and reports the main performance comparisons. Section 2.7 concludes.

2.2 Literature Review

Hedge Fund Replication. The hedge fund replication literature seeks to construct portfolios that mimic hedge fund returns using transparent, liquid instruments. Early and seminal work includes Fung & Hsieh (2001, 2004) (although more concerned with style identification than pure replication), who propose primitive trend-following strategies to replicate hedge fund styles. Hasanhodzic & Lo (2007) evaluate factor-based replication and find that linear

models can capture a substantial portion of hedge fund returns, though alpha remains elusive.

Fung & Hsieh (2008) develop replication strategies based on asset-backed securities, volatility, and credit spreads, achieving moderate success in matching aggregate hedge fund index returns. Kat & Palaro (2007) construct replication portfolios from options and other derivatives. These studies generally conclude that replication can approximate hedge fund return distributions but may not fully capture alpha or extreme tail risk.

More recent work estimates time-varying exposures to improve replication accuracy. Bollen & Whaley (2009) employ optimal changepoint regression and state-space models to track dynamic factor loadings. Lambert & Platania (2020) use state-space methods to model hedge fund exposures as functions of macroeconomic variables, finding that exposures respond systematically to changes in market conditions. O'Doherty *et al.* (2017) and Duanmu *et al.* (2020) use rolling-window regressions to estimate time-varying exposures and construct replication strategies, with mixed success.

Billio *et al.* (2012) employ regime-switching models to capture changes in hedge fund exposures across different equity market regimes, finding that most strategies increase exposure to market, credit spread, and volatility factors during high-volatility regimes. Patton & Ramadorai (2013) model dynamic exposures as linear functions of observable state variables, documenting significant intra-month variation in hedge fund betas.

Our approach builds on these dynamic exposure estimation methods but introduces cross-sectional dispersion as a novel conditioning variable. By exploiting heterogeneity in positioning across funds, we identify periods when aggregate exposure estimates are more reliable and replication strategies are more profitable.

Time-Series Momentum. Time-series momentum - an asset's own past returns predict its future returns - has been extensively documented across markets. Moskowitz *et al.* (2012) provide comprehensive evidence that a diversified portfolio of time-series momentum strategies across commodity, equity, fixed income, and currency futures generates substantial risk-adjusted returns with limited exposure to standard risk factors. The profitability persists across subperiods and is present in both developed and emerging markets.

Hurst *et al.* (2017) examine managed futures strategies, which are closely related to time-series momentum, and find that these strategies exhibit positive returns during both trending and crisis periods. The strategies' performance is robust to various implementation choices, including lookback periods and

position sizing rules. Baltas & Kosowski (2013) explore the diversification benefits of combining momentum signals across different asset classes, while Babu *et al.* (2020) document that trends are pervasive across virtually all liquid asset classes.

Several studies investigate potential improvements to basic time-series momentum. Goulding *et al.* (2023b,a) propose blending fast and slow momentum signals to better navigate momentum turning points. Kim *et al.* (2016) argue that much of the performance of cross-asset momentum strategies derives from volatility scaling, a finding consistent with Moreira & Muir (2017), who show that scaling equity positions inversely with recent volatility substantially improves risk-adjusted returns.

The performance of momentum strategies varies across economic conditions. Hutchinson & O'Brien (2020) find that time-series momentum returns are lower during periods of elevated macroeconomic uncertainty. Cujean & Hasler (2017) develop a theoretical model in which momentum is more pronounced during bad times and when uncertainty is high, as arbitrageur trades reveal information more distinctly.

2.3 Data

The data for this essay is taken from Chapter 1. The sample consists of 438 unique Brazilian macro hedge funds spanning January 2006 to August 2024. Daily fund returns are obtained from the Brazilian Securities Commission (CVM) database.

Risk factor returns are constructed from liquid Brazilian futures contracts and US market indices. The factors include Brazilian equities (BXMKT), the BRL/USD exchange rate (USD), 1-year Brazilian nominal bonds (BXBOND1Y), 5-year Brazilian nominal bonds (BXBOND5Y), 5-year Brazilian inflation-linked bonds (BXINF5Y), US equities (USMKT), and US 5-year bonds (USBOND5Y). With the exception of USMKT and USBOND5Y, all factors represent investable assets with daily prices. All replication strategies considered in this essay take position only in the risk factor directly related to Brazilian markets: BXMKT, USD, BXBOND1Y, BXBOND5Y and BXINF5Y. On the other hand, 4-factor alhoa is always computed controlling for BXMKT, BXBOND5Y, USMKT and USBOND5Y.

Time-varying risk exposures for each fund are estimated using the optimal changepoint regression methodology described in Chapter 1. Aggregate exposures are computed as NAV-weighted averages across all active funds each month. Cross-sectional dispersion is measured as the standard deviation of es-

timated exposures across funds for each risk factor and month.

2.4 Time-Series Momentum

Before examining hedge fund replication strategies, we establish that time-series momentum strategies generate significant excess returns in the Brazilian market, consistent with international evidence. This serves two purposes: (1) it provides a benchmark for evaluating hedge fund replication performance, and (2) it confirms that the momentum anomaly documented in US and global markets extends to Brazilian futures.

Table 2.1 presents regressions of monthly risk factor returns on their own 12 monthly lags. Several factors exhibit significant autocorrelation at short horizons. BXMKT shows positive 1-month autocorrelation (0.1405, t = 2.10) and negative 9-month autocorrelation (-0.1392, t = -2.14). BXBOND1Y displays positive coefficients at lags 1 and 3, both statistically significant. USD exhibits positive 2-month autocorrelation (0.1341, t = 2.46). These patterns suggest potential profitability for time-series momentum strategies targeting different lookback windows.

Table 2.2 reports the performance of time-series momentum strategies across different lookback horizons (1, 3, 6, and 12 months) for each risk factor individually and for a diversified multi-factor portfolio. The strategy is implemented as follows: at the end of each month, if the cumulative return over the lookback period is positive, a long position is taken; if negative, a short position. Individual factor strategies are evaluated against a buy-and-hold benchmark in the respective factor, while the diversified multi-factor strategy is assessed relative to a 4-factor model (BXMKT, BXBOND5Y, USBOND5Y, USMKT). In the diversified multi-factor strategy, all individual positions are scaled to achieve 10% ex-ante trailing volatility, following Moskowitz *et al.* (2012).

The results confirm that time-series momentum generates significant alpha in Brazilian markets. The diversified strategy achieves the strongest performance across all horizons, with 1-month, 3-month, and 6-month strategies all yielding significant alphas. The 6-month lookback period delivers an alpha of 4.12% (t-statistic = 2.30) with a Sharpe ratio of 0.60. Individual factor strategies show heterogeneous performance: BXBOND1Y exhibits consistent positive alpha across multiple horizons, while USD momentum is profitable only at the 6-month horizon (8.36%, t = 2.50). BXBOND5Y shows significant alpha at the 1-month horizon (4.64%, t = 2.15).

These findings confirm that time-series momentum strategies, widely

Table 2.1: Regression of returns on lagged returns

Lag (months)	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y
1	**0.1405**	0.0243	**0.1833**	0.0883	0.0310
	(2.10)	(0.20)	**(2.34)**	(1.71)	(0.32)
2	-0.0817	**0.1341**	0.1210	-0.1016	-0.0212
	(-1.21)	**(2.46)**	(1.81)	(-0.86)	(-0.24)
3	-0.0514	-0.0035	**0.1815**	-0.0013	-0.0328
	(-0.67)	(-0.06)	**(2.83)**	(-0.02)	(-0.34)
4	-0.0546	-0.0155	-0.0229	-0.0513	-0.0675
	(-0.83)	(-0.29)	(-0.43)	(-0.65)	(-1.23)
5	-0.0441	-0.0207	0.0654	0.0357	0.0403
	(-0.70)	(-0.30)	(1.10)	(0.57)	(0.56)
6	0.0033	0.0863	0.0479	0.0559	0.0013
	(0.04)	(1.19)	(0.89)	(0.64)	(0.02)
7	-0.0031	-0.0458	0.0335	-0.0364	0.0490
	(-0.04)	(-0.63)	(0.43)	(-0.51)	(0.74)
8	-0.0283	-0.0765	0.0671	-0.0163	-0.0362
	(-0.42)	(-1.06)	(1.12)	(-0.27)	(-0.58)
9	**-0.1392**	-0.0294	-0.0015	-0.0196	-0.0839
	(-2.14)	(-0.53)	(-0.02)	(-0.39)	(-0.95)
10	0.0180	-0.0044	-0.0714	0.0109	-0.0872
	(0.32)	(-0.08)	(-1.20)	(0.18)	(-1.51)
11	0.0771	0.0297	0.0124	-0.0196	0.0312
	(1.31)	(0.53)	(0.28)	(-0.37)	(0.56)
12	-0.0291	-0.0380	-0.0276	-0.0395	-0.0606
	(-0.46)	(-0.52)	(-0.52)	(-0.65)	(-0.88)

Note: This table presents coefficients and t-statistics (in parentheses, Newey-West adjusted) from regressing monthly returns of each risk factor on its 12 monthly lags. Coefficients with t-statistics above 1.96 in absolute value (significant at the 5% level) are highlighted.

documented in US and global markets, extend to Brazilian assets commonly traded by macro hedge funds. The multi-factor diversified 6-month strategy serves as the benchmark against which we evaluate hedge fund replication strategies in subsequent sections.

2.5 Hedge Fund Replication Strategy

Having established the performance of time-series momentum, we now examine the actual performance of aggregate macro hedge funds and construct basic replication strategies based on estimated exposures.

Table 2.2: Performance of time-series momentum strategies

Lookback	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y	Diversified
1	7.87%	-0.38%	0.75%	**4.64%**	1.66%	**5.77%**
	(1.55)	(-0.09)	(1.77)	**(2.15)**	(1.19)	**(3.27)**
3	8.58%	1.27%	**0.96%**	1.11%	1.11%	**4.50%**
	(1.89)	(0.34)	**(2.26)**	(0.42)	(0.78)	**(2.71)**
6	-8.15%	**8.36%**	**1.03%**	3.77%	0.34%	**4.12%**
	(-1.36)	**(2.50)**	**(2.51)**	(1.74)	(0.26)	**(2.30)**
12	-4.01%	-0.57%	**0.86%**	-0.28%	-0.64%	1.75%
	(-0.62)	(-0.14)	**(2.19)**	(-0.11)	(-0.44)	(0.94)

Notes: This table presents annualized alphas and t-statistics (in parentheses, Newey-West adjusted) for time-series momentum strategies applied to each risk factor and to a diversified portfolio. Individual alphas computed vs buy-and-hold strategy in the respective risk factor. Diversified alpha computed vs 4-factor model (BXMKT, BXBOND5Y, USBOND5Y, USMKT). Each factor exposure in diversified portfolio is scaled to 10 percent ex-ante trailing volatility. Bold values indicate statistical significance at the 5% level.

2.5.1 Actual Hedge Fund Performance

Table 2.3 presents the 4-factor alpha for aggregate macro hedge fund portfolios. Two weighting schemes are considered: equal-weighted (simple average across funds) and NAV-weighted (using assets under management as weights). Both portfolios exhibit positive alpha, though the magnitude and statistical significance differ substantially.

Table 2.3: Actual macro hedge funds aggregate performance

Metric	Equal-Weighted	NAV-Weighted
Alpha (Annualized)	1.03%	**3.18%**
	(1.85)	**(4.75)**

Note: This table presents alpha coefficients and t-statistics (in parentheses, Newey-West adjusted) from regressing monthly aggregate macro hedge fund returns on 4-factor model (BXMKT, BXBOND5Y, USBOND5Y, USMKT). Equal-weighted uses simple average across funds. NAV-weighted uses assets under management as weights. Bold values indicate statistical significance at the 5% level.

The NAV-weighted portfolio generates a highly significant alpha of 3.18% (t-statistic = 4.75), indicating that larger funds, which receive greater weight in the aggregate, deliver substantial risk-adjusted excess returns beyond what can be explained by systematic exposures to equity and bond markets. The equal-weighted portfolio shows an alpha of 1.03% (t-statistic = 1.85). The difference suggests that larger hedge funds may have access to superior information, execution, or strategies.

These results motivate the replication exercise: if hedge fund positioning contains valuable information, strategies that mimic their exposures should capture at least a portion of this alpha.

2.5.2 Predictive Regressions

To assess whether hedge fund exposures predict factor returns, Table 2.4 presents regressions of monthly returns on lagged aggregate NAV-weighted exposures. For each risk factor i and month t, we estimate:

$$r_{i,t} = \alpha_i + \beta_i \cdot \text{HF_Exposure}_{i,t-1} + \varepsilon_{i,t} \tag{2.1}$$

where $r_{i,t}$ is the factor return and $\text{HF_Exposure}_{i,t-1}$ is the aggregate hedge fund exposure estimated via Kalman filter in the previous month.

Table 2.4: Regression of returns on lagged hedge fund estimated exposures

HF Exposure	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y
HF risk exposure to factor	-0.0323 (-0.20)	0.0365 (0.68)	-0.0008 (-0.74)	0.0414 (1.83)	-0.0366 (-1.08)

Notes: This table presents coefficients and t-statistics (in parentheses, Newey-West adjusted) from regressing monthly returns of each risk factor on its lagged aggregate macro hedge fund estimated exposure. Bold values indicate statistical significance at the 5% level.

The coefficients reveal limited unconditional predictability. Only BXBOND5Y reaches statistical significance (at a 10% level), with a coefficient of 0.0414 (t-statistic = 1.83), suggesting that higher aggregate exposure to 5-year bonds predicts positive bond returns. The coefficients for BXMKT, USD, BXBOND1Y, and BXINF5Y are small in magnitude and statistically insignificant. These results indicate that a simple strategy of following aggregate hedge fund positioning may not reliably generate excess returns.

2.5.3 Simple Replication Strategy Results

Despite the weak unconditional predictability in Table 2.4, We construct a simple replication strategy to serve as a baseline. At the end of each month, the strategy takes positions in each risk factor proportional to the lagged aggregate exposure. The diversified portfolio is the combination of all the individual exposures.

Table 2.5 reports the performance of this simple replication strategy. Individual risk factor strategies exhibit modest and generally insignificant

alphas. BXBOND5Y shows the strongest performance with an alpha of 0.21% (t-statistic = 1.70), consistent with the positive coefficient in Table 2.4. The diversified portfolio achieves an alpha of 0.49% (t-statistic = 1.21), capturing only a small fraction of the 3.18% alpha generated by the actual NAV-weighted hedge fund portfolio.

Table 2.5: Performance of hedge fund replication strategy

Metric	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y	Diversified
Alpha (Annualized)	-0.06% (-0.23)	0.15% (0.67)	-0.00% (-0.03)	0.21% (1.70)	-0.05% (-1.16)	0.49% (1.21)

Note: This table presents performance metrics for a simple hedge fund replication strategy applied to each risk factor and to a diversified portfolio (combining all 5 exposures). Alpha is reported as annualized percentage. Individual alphas vs buy-and-hold. Diversified alpha vs 4-factor model. Bold values indicate statistical significance at the 5% level. Newey-West adjusted t-statistics are presented in parenthesis.

The modest performance of the simple replication strategy suggests that unconditional use of lagged exposures is insufficient. This motivates the investigation of whether conditioning on cross-sectional dispersion can improve results.

2.6 Hedge Fund Replication with Dispersion Conditioning

The weak performance of the unconditional replication strategy raises the question: when is aggregate hedge fund positioning most informative? We hypothesize that cross-sectional dispersion in exposures provides a signal about information quality. When dispersion is low, hedge funds are more aligned in their positioning, potentially reflecting stronger conviction. High dispersion may indicate disagreement among managers. Alternatively, dispersion can be interpreted as measuring the signal-to-noise ratio in aggregate exposure estimates: low dispersion suggests a cleaner signal.

2.6.1 Dispersion-Conditional Predictability

To test whether predictability varies with dispersion, we modify the regressions in Table 2.4 by interacting lagged exposures with a dispersion indicator. For each risk factor and month, dispersion is measured as the cross-sectional standard deviation of estimated exposures across all active funds. We define a high-dispersion indicator that equals one when dispersion exceeds its trailing 36-month median and zero otherwise. The regression specification

becomes:

$$r_{i,t} = \alpha_i + \beta_i^H \cdot \text{HF_Exposure}_{i,t-1} \times I_{i,t-1}^H + \beta_i^L \cdot \text{HF_Exposure}_{i,t-1} \times I_{i,t-1}^L + \varepsilon_{i,t} \tag{2.2}$$

where $I_{i,t-1}^H$ and $I_{i,t-1}^L$ are indicators for high and low dispersion, respectively.

Table 2.6 presents the results. The pattern is striking: for BXMKT, the coefficient during low-dispersion periods is 0.8840 (t-statistic = 2.15), while the coefficient during high-dispersion periods is -0.0145 (t-statistic = -0.09). This indicates that hedge fund equity exposure significantly predicts subsequent equity returns when funds are aligned, but exhibits no predictive power when dispersion is high. Similar patterns appear for other factors (but not all), though the differences are less pronounced. The coefficient for BXBOND5Y during low-dispersion periods is 0.0443 (t-statistic = 1.69), compared to 0.0158 (t-statistic = 0.36) during high dispersion.

Table 2.6: Regression of returns on lagged hedge fund estimated exposures interacted with dispersion measure

HF Exposure x Dispersion	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y
HF exposure - high dispersion	-0.0145	0.0171	0.0001	0.0158	-0.0215
	(-0.09)	(0.25)	(0.12)	(0.36)	(-0.68)
HF exposure - low dispersion	**0.8840**	-0.0088	0.0004	0.0443	-0.0193
	(2.15)	(-0.07)	(0.26)	(1.69)	(-0.34)

Note: This table presents coefficients and t-statistics (in parentheses, Newey-West adjusted) from regressing monthly returns of each risk factor on its lagged aggregate macro hedge fund estimated exposure interacted with a measure of hedge fund exposure dispersion. Dispersion with respect to a risk factor is deemed high when the cross-section standard deviation of exposure estimates is above its trailing 36-month median. Bold values indicate statistical significance at the 5% level.

These findings motivate replication strategies that condition on dispersion, exploiting the stronger predictability during low-dispersion periods.

2.6.2 Binary Dispersion Conditioning

The first conditioning approach implements a binary rule: a position is only taken when dispersion is low. Specifically, for each risk factor, the strategy follows the lagged aggregate exposure if dispersion is below its trailing 36-month median, and holds zero exposure otherwise. This ensures that positions are taken only when hedge funds exhibit alignment in their positioning.

Table 2.7 reports the performance of this binary conditioning strategy. The diversified portfolio achieves an alpha of 0.54% (t-statistic = 1.83), with a much stronger level of statistical significance than the unconditional strategy's. The strategy appears to benefit from avoiding positions during high-dispersion

periods when predictability may be weaker. BXBOND5Y continues to show the strongest individual factor performance with an alpha of 0.19% (t-statistic = 1.59).

Table 2.7: Performance of hedge fund replication strategy with binary conditioning on dispersion

Metric	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y	Diversified
Alpha (Annualized)	0.15% (0.91)	-0.02% (-0.11)	0.01% (0.11)	0.19% (1.59)	-0.01% (-0.40)	0.54% (1.83)

Note: This table presents performance metrics for a hedge fund replication strategy that conditions on measure of exposure dispersion. Individual risk factor estimated exposure is only replicated if dispersion is below its trailing 36-month mean. Alpha is reported as annualized percentage. Individual alphas vs buy-and-hold. Diversified alpha vs 4-factor model. Bold values indicate statistical significance at the 5% level. Newey-West adjusted t-statistics are presented in parenthesis.

2.6.3 Inverse Dispersion Scaling

The binary approach discards information by treating all high-dispersion periods identically. A more refined strategy scales positions continuously with dispersion. We implement a scaling rule where the position size is inversely related to dispersion:

$$\text{Position}_{i,t} = \text{HF_Exposure}_{i,t-1} \times \left(1 - \frac{\text{Dispersion}_{i,t-1} - \text{Dispersion}_{i,\min}}{\text{Dispersion}_{i,\max} - \text{Dispersion}_{i,\min}}\right) \tag{2.3}$$

where $\text{Dispersion}_{i,\min}$ and $\text{Dispersion}_{i,\max}$ are the minimum and maximum dispersion over the trailing 36 months. This formula produces a scaling coefficient ranging from 0 (when dispersion is at its trailing maximum) to 1 (when dispersion is at its trailing minimum).

Table 2.8 presents the results. The continuous scaling strategy achieves a diversified portfolio alpha of 0.34% (t-statistic = 1.96), significant a t 1 5% level.

2.6.4 Performance Comparison

Table 2.9 provides a comprehensive comparison of all strategies, scaled to 10% ex-post volatility for comparability. The table includes the 6-month time-series momentum benchmark (TS-MOM-6M), actual aggregate hedge fund portfolios (equal-weighted HF-EW and NAV-weighted HF-SW), the simple replication strategy (HF-REP), and the two dispersion-conditional strategies

Table 2.8: Performance of hedge fund replication strategy scaling by dispersion

Metric	BXMKT	USD	BXBOND1Y	BXBOND5Y	BXINF5Y	Diversified
Alpha (Annualized)	0.02% (0.43)	0.02% (0.56)	0.00% (0.01)	0.01% (0.15)	-0.01% (-0.40)	0.34% (1.96)

Note: This table presents performance metrics for a hedge fund replication strategy that scales holdings by a measure of exposure dispersion. Individual risk factor estimated exposure is multiplied by a scaling coefficient ranging from 0 (if dispersion is near its trailing 36-month maximum) to 1 (if dispersion is near its trailing 36-month minimum). Alpha is reported as annualized percentage. Individual alphas vs buy-and-hold. Diversified alpha vs 4-factor model. Bold values indicate statistical significance at the 5% level. Newey-West adjusted t-statistics are presented in parenthesis.

(HF-REP-DBIN for binary conditioning and HF-REP-DCONT for continuous scaling).

Several findings emerge. First, the actual NAV-weighted hedge fund portfolio (HF-SW) delivers the strongest performance, with a mean return of 10.99% and a 4-factor alpha of 10.13% (t-statistic = 4.75). Even after controlling for both the 4-factor model and time-series momentum, the alpha remains highly significant at 8.98% (t-statistic = 4.04). This indicates that hedge funds generate substantial excess returns that cannot be explained by passive exposures or simple momentum strategies.

Second, the dispersion-conditional replication strategies substantially outperform the unconditional approach. The continuous scaling strategy (HF-REP-DCONT) achieves an alpha of 5.09% (t-statistic = 1.96) versus 2.22% (t-statistic = 1.21) for the simple strategy. The Sharpe ratio improves from 0.36 to 0.57, and the maximum drawdown decreases from -21.24% to -16.96%. The binary conditioning strategy (HF-REP-DBIN) shows similar improvements with an alpha of 5.30% (t-statistic = 1.83). While these improvements fall just short of conventional significance levels, they represent economically meaningful enhancements in both returns and risk characteristics.

Third, when controlling for time-series momentum, the dispersion-conditional strategies maintain notable alpha. HF-REP-DBIN achieves an alpha of 4.60% (t-statistic = 1.71) and HF-REP-DCONT generates 4.02% (t-statistic = 1.72) after accounting for momentum. This demonstrates that the dispersion signal provides information that is distinct from standard momentum strategies and is not simply capturing trend-following behavior.

Fourth, the risk profile improves substantially with dispersion conditioning. Both conditional strategies exhibit maximum drawdowns around -16.5% to -17.0%, compared to -21.24% for the simple replication strategy and -22.74% for pure time-series momentum. This suggests that conditioning on dispersion

Table 2.9: Performance comparison of all strategies

Metric	TS-MOM-6M	HF-EW	HF-SW	HF-REP	HF-REP-DBIN	HF-REP-DCONT
Mean Return	5.96%	5.07%	10.99%	3.55%	5.10%	5.70%
Alpha vs 4-Factor	**5.68%** **(2.30)**	3.40% (1.85)	**10.13%** **(4.75)**	2.22% (1.21)	5.30% (1.83)	5.09% (1.96)
Alpha vs 4-Factor + TS-MOM	-	2.79% (1.56)	**8.98%** **(4.04)**	1.13% (0.62)	4.60% (1.71)	4.02% (1.72)
Sharpe Ratio	0.60	0.51	1.10	0.36	0.51	0.57
Max Drawdown	-22.74%	-33.35%	-19.60%	-21.24%	-16.54%	-16.96%
N	218	219	219	218	183	183

Note: This table presents performance metrics for the following strategies/portfolios: a diversified time-series momentum with 6-month lookback (TS-MOM-6M), actual equal-weighted aggregate macro hedge fund return (HF-EW), actual NAV-weighted macro hedge fund return (HF-SW), a simple replication strategy conditioned on lagged estimated risk exposure (HF-REP), a replication strategy where estimated risk exposure is only replicated if dispersion is low (HF-REP-DBIN) and a replication strategy that scales exposures inversely with exposure dispersion (HF-REP-DCONT). Alpha vs 4-factor model and expressed as annualized percentage. Bold values indicate statistical significance at the 5% level. Newey-West adjusted t-statistics are presented in parenthesis. All strategies scaled to 10% ex-post annual volatility.

helps avoid periods of weak performance.

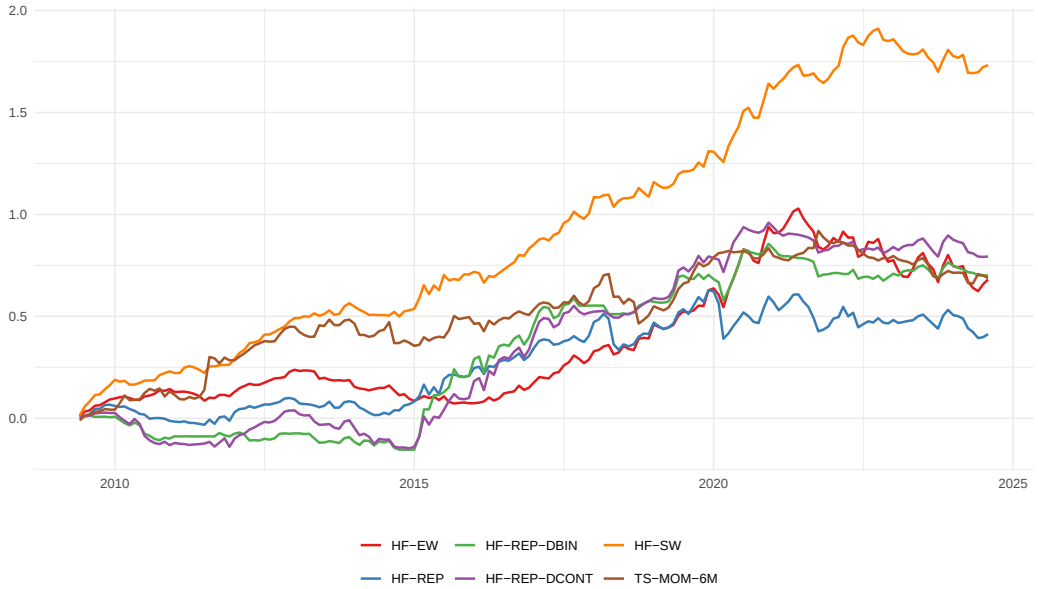
Figure 2.1 presents cumulative returns for all strategies, illustrating the superior and more stable growth of the dispersion-conditional approaches.

2.7 Conclusion

This essay demonstrates that cross-sectional dispersion in hedge fund risk exposures contains valuable information for constructing replication strategies. A simple strategy that follows aggregate hedge fund estimated positioning yields modest performance, with a 4-factor alpha that is not statistically significant at conventional levels and Sharpe ratio of 0.36. However, conditioning on dispersion, measured as the standard deviation of estimated exposures across funds, substantially improves results. Strategies that scale positions inversely with dispersion achieve alphas with t-statistics approaching 2.0 and Sharpe ratios of 0.51 to 0.57. The economic magnitude of the improvement is substantial.

Two interpretations of the dispersion signal merit further investigation. First, low dispersion may reflect stronger conviction or agreement among hedge fund managers about optimal positioning, making aggregate exposures a more reliable signal. Second, dispersion can be viewed as measuring noise in the estimated aggregate exposure: when funds are more dispersed, the aggregate measure is less precise and less informative. Both interpretations are consistent

Figure 2.1: Strategies cumulative returns



Note: Figure plots cumulative returns of actual aggregate macro hedge fund portfolios, time-series momentum and macro hedge fund replication strategies.

with our findings and merit deeper investigation in future research.

3
Exploring the Cross-section of Brazilian Hedge Fund Returns: Risk-factor Timing Intensity

Abstract. This essay investigates whether risk factor timing intensity predicts cross-sectional returns among Brazilian macro hedge funds. Adapting the active share concept from equity mutual funds to the hedge fund context, we construct a time-series risk factor timing intensity measure (TSACT) that quantifies the tracking error between returns implied by time-varying versus assumed-constant factor exposures. Using daily data on 438 Brazilian macro hedge funds from January 2006 to August 2024, we test whether TSACT predicts future returns alongside two benchmark measures of hedge fund distinctiveness: correlation and beta with respect to aggregate hedge fund returns. Using a Fama-MacBeth regression procedure, we find that TSACT significantly predicts monthly excess returns, even after controlling for fund characteristics, risk factor loadings, and fees. This relationship persists for extended 6-month holding periods. In contrast, distinctiveness measures (HFCORR and HFBETA) exhibit no significant predictive power.

Keywords: active share; market timing; hedge funds; risk exposures; cross-sectional returns

3.1 Introduction

The active share literature, pioneered by Cremers & Petajisto (2009), demonstrates that equity mutual funds with higher deviations from their benchmarks generate superior risk-adjusted returns. This finding suggests an underlying mechanism: active management adds value when managers express conviction through portfolio positions that meaningfully differ from passive alternatives. However, applying this concept to hedge funds, particularly macro hedge funds, presents unique challenges. Unlike equity mutual funds with well-defined benchmarks, macro hedge funds operate dynamically across multiple asset classes without an obvious ex-ante benchmark.

Yet, macro hedge funds offer a compelling setting to investigate conviction and risk taking. Macro hedge funds express views about macroeconomic conditions by continuously adjusting exposures to equities, currencies, interest rates and other fundamental assets. The dynamic nature of their trading suggests that funds exhibiting greater time-variation in their risk exposures may be actively trading on better information, potentially leading to superior performance. This conjecture motivates our central research question: does active repositioning of risk exposures predict cross-sectional returns among macro hedge funds?

This essay tests whether risk factor timing intensity predicts cross-sectional returns using monthly data on 438 Brazilian macro hedge funds spanning January 2006 to August 2024. We employ the optimal changepoint methodology from Chapter 1 to estimate time-varying factor exposures for each fund across seven risk factors: Brazilian equities, Brazilian nominal bonds (1-year and 5-year), Brazilian inflation-linked bonds, the BRL/USD exchange rate, US equities, and US bonds. These time-varying exposure estimates enable us to construct a novel risk factor timing intensity measure.

We propose TSACT (time-series "activeness", a risk factor timing intensity measure), defined as the tracking error between returns implied by a fund's time-varying factor exposure estimates and returns implied by assumed-constant (average) exposures over a rolling 36-month window. Funds with higher TSACT values are taking on more risk relative to the hypothetical where they kept risk exposures constant - potentially suggesting more active information-based trading.

We also compare "activeness", or risk factor timing intensity, with distinctiveness, another predictive mechanism explored in the literature. As proposed by Sun *et al.* (2012), distinctiveness measures a given hedge fund's degree of correlation or co-movement within its peer group. Funds that have a lower cor-

relation with other funds in the same style are found to exhibit higher future returns. In our setting, we construct two benchmark measures of distinctiveness: HFCORR (correlation with aggregate hedge fund returns) and HFBETA (beta with respect to aggregate hedge fund returns).

We test the predictive power of these measures using Fama-MacBeth cross-sectional regressions and univariate portfolio sorts. The regression framework allows control for multiple fund characteristics, factor loadings, and fees, while portfolio sorts provide a complementary non-parametric assessment of the timing intensity-return relationship.

Main Results. We report four key findings. First, TSACT significantly predicts monthly excess returns in Fama-MacBeth regressions. The univariate coefficient on lagged TSACT is positive with Newey-West adjusted t-statistic of 2.16, indicating that funds with higher time-series risk factor timing intensity earn significantly higher future returns. This relationship remains robust and statistically significant in multivariate specifications after controlling for HFCORR, HFBETA, fund volatility, factor loadings to main risk factors - BXMKT, BXBOND5Y, USMKT and UXBOND5Y - fund size, age, management fees, and performance fees. Estimated coefficients range from 0.84 to 1.11, indicating that a 1 p.p. higher TSACT (expressed as an annualized tracking error) yields around 0.8-1.1 p.p. higher annualized excess returns.

Second, the relationship persists when extending the holding period from 1 to 6 months. To avoid concerns about overlapping observations, we run Fama-McBeth cross-section regression using returns and observations over non-overlapping six-month periods.

Third, while TSACT predicts returns in cross-sectional regressions, univariate portfolio sorts on TSACT fail to generate significant four-factor alpha. Equal-weighted quintile portfolios sorted on lagged TSACT exhibit a spread of 0.57% (t-statistic = 0.37) between the highest and lowest quintiles. This disconnect between regression and sorting evidence reveals a nuanced pattern that suggests that the timing intensity-return relationship operates through interactions with other fund characteristics rather than manifesting as a simple monotonic pattern across TSACT quintiles.

Bivariate portfolio sorts support this interpretation. When funds are first grouped by average volatility (low, medium, high) and then sorted into TSACT quintiles within each volatility group, the timing intensity-return relationship emerges most strongly in the medium volatility group. Within this group, the TSACT spread (Q5-Q1) delivers a four-factor annualized alpha of 1.64% (t-statistic = 2.39), statistically significant at the 5% level. In contrast, the

high TSACT quintile underperforms in the low volatility group (annualized alpha = -0.44%, t-statistic = -1.63), potentially reflecting measurement error in estimated risk exposures that contaminates the TSACT signal when true fund volatility is low. In the high volatility group, the TSACT spread (Q5-Q1) delivers a four-factor annualized alpha of 4.03% (t-statistic = 1.19), potentially large but failing to achieve statistical significance at conventional levels.

Fourth, the distinctiveness measures (HFCORR and HFBETA) exhibit no significant predictive power in almost all specifications. Univariate Fama-MacBeth regressions yield coefficients that do not reach statistical significance at conventional levels. Portfolio sorts confirm this absence of predictive power, with HFCORR and HFBETA quintile spreads producing four-factor alphas of 0.41% (t-statistic = 0.68) and 0.83% (t-statistic = 0.45), respectively. These results indicate that distinctiveness does not seem to predict superior performance in the Brazilian macro hedge fund context.

Contribution. This essay makes three contributions to the literature. First, it extends the active share concept to macro hedge funds by constructing a time-series risk factor timing intensity measure based on estimates of dynamic risk exposures. While Cremers & Petajisto (2009) measure risk factor timing intensity as deviation from benchmark portfolio holdings, macro hedge funds lack clear portfolio benchmarks. Our TSACT measure sidesteps this issue by quantifying the extent to which funds dynamically adjust their systematic risk exposures over time. This represents, as far as we know, the first application of active share principles to Brazilian macro hedge funds. Our work is conceptually similar to Duanmu *et al.* (2018), who examine risk factor timing intensity among US hedge funds. However, we differ in the way we construct the "activeness" measure: while they propose a composite of changes in betas estimated from rolling-window regressions on monthly data, we leverage the tracking error concept to put forth a measure of timing intensity that is economically more intuitive.

Second, the essay contributes to the hedge fund return forecasting literature by demonstrating that time-series risk factor timing intensity predicts cross-sectional returns even after controlling for established predictors. Prior work documents that systematic risk exposure (Bali *et al.*, 2011), liquidity timing (Cao *et al.*, 2013), macroeconomic risk sensitivity (Bali *et al.*, 2014), distinctiveness (Sun *et al.*, 2012), sentiment beta (Chen *et al.*, 2021), among other variables, predict hedge fund returns. Our findings show that TSACT also adds incremental predictive power, suggesting that dynamic repositioning behavior contains information not captured by exposures alone.

Third, the results provide empirical support for the "conviction" pillar of active management identified by Cremers *et al.* (2019). Cremers argues that successful active management requires skill, conviction, and opportunity, where conviction manifests as willingness to take large active positions. In the hedge fund context, conviction translates to dynamic repositioning of risk exposures in response to changing information. Our finding that TSACT predicts returns, particularly when interacted with fund volatility, demonstrates that active repositioning can enhance performance when executed within an appropriate risk framework.

3.1.1 Overview

The remainder of this essay proceeds as follows. Section 2 reviews the literature on hedge fund return predictors and active share. Section 3 describes the data, which draws on the hedge fund sample and risk factor exposures estimated in Essay 1. Section 4 defines the risk factor timing intensity measure and distinctiveness benchmarks (TSACT, HFCORR, HFBETA) and presents descriptive statistics. Section 5 reports Fama-MacBeth cross-sectional regressions testing the predictive power of these measures. Section 6 presents portfolio sorts providing complementary evidence on the timing intensity-return relationship. Section 7 concludes and discusses extensions.

3.2 Literature Review

Active Share and Fund Performance. The active share literature, pioneered by Cremers & Petajisto (2009), demonstrates that equity mutual funds with higher deviations from their benchmarks generate superior risk-adjusted returns. Petajisto (2013) further shows that active share predicts fund performance even after controlling for fund characteristics and past returns, with the most active funds significantly outperforming passive index funds while closet indexers underperform after fees. These findings establish that active management adds value when managers express conviction through portfolio positions that meaningfully differ from passive alternatives.

Cremers *et al.* (2019) synthesize two decades of active management research, identifying three pillars of successful active management: skill, conviction, and opportunity. Skill refers to a manager's ability to identify mispriced securities or macro trends. Conviction manifests as willingness to deviate meaningfully from benchmarks through concentrated positions or factor

tilts. Opportunity reflects the breadth of investment choices and the degree of market inefficiency. Our TSACT measure captures the conviction dimension in the hedge fund context: funds exhibiting greater time-variation in risk exposures demonstrate conviction by actively repositioning in response to changing information.

Hedge Fund Return Predictors. A substantial literature investigates predictors of hedge fund returns in the cross-section. Bali *et al.* (2012) demonstrate that funds' exposures to systematic risk factors predict future returns. Analyzing exposure to macroeconomic factors, Bali *et al.* (2011) finds that exposure to default risk and inflation predict hedge fund returns while Bali *et al.* (2011) finds that funds with higher exposure to macroeconomic uncertainty earn higher subsequent returns. Cao *et al.* (2013) show that funds exhibiting liquidity timing ability (reducing exposure during illiquid periods) earn higher risk-adjusted returns. Chen *et al.* (2021) document that funds with higher sentiment beta outperform during optimistic periods, suggesting that funds trading on behavioral biases generate superior returns. Bali *et al.* (2018) find that funds offering greater upside potential earn higher future returns, consistent with investor preference for positive skewness. These studies establish that dynamic adjustment of risk exposures (whether to market conditions, liquidity, sentiment, or macroeconomic uncertainty) relates to fund performance.

Of particular relevance to our study, Sun *et al.* (2012) propose that strategic distinctiveness predicts hedge fund performance. They construct a distinctiveness measure capturing the extent to which a fund's return pattern differs from its peers within a strategy category, finding that more distinctive funds earn higher risk-adjusted returns. The authors interpret this as evidence that funds deviating from consensus positioning possess superior information or skill. Titman & Tiu (2011) examine hedge fund holdings and find that funds holding distinct positions relative to other hedge funds earn higher returns, though the relationship varies across market conditions. Recent work by Duanmu *et al.* (2018) examines risk factor timing intensity among US hedge funds, measuring a composite of the differences in betas estimated over overalapping rolling windows.

In the case of Brazilian hedge funds, previous research has documented that some Brazilian hedge funds exhibit abnormal returns and persistent performance. Jordão & Moura (2011) analyze performance of Brazilian hedge funds from 2002 to 2009, finding that macro funds generate positive risk-adjusted returns and exhibit performance persistence at shorter horizons.

Joaquim & Moura (2011) examine Brazilian hedge fund performance during the 2008 financial crisis, documenting that top-performing funds maintained their relative rankings even during the crisis period, suggesting genuine skill rather than luck. More recently, Almeida *et al.* (2021) investigate tail risk exposures of Brazilian hedge funds, finding that funds actively manage their tail risk exposures and that changes in these exposures correlate with future returns.

3.3 Data

This essay employs the hedge fund sample and risk factor exposures estimated in Chapter 1. The sample comprises 438 unique Brazilian macro hedge funds with daily returns spanning January 2006 to August 2024, covering 224 months.

For each fund, Chapter 1 estimates time-varying exposures to seven risk factors using an optimal changepoint regression procedure. The risk factors include Brazilian equities (BXMKT), the BRL/USD exchange rate (USD), Brazilian interest rates with 1-year and 5-year constant maturities (BXBOND1Y and BXBOND5Y), Brazilian inflation-linked bonds with 5-year target maturity (BXINF5Y), US equities (USMKT), and US bonds with 5-year constant maturity (USBOND5Y).

The optimal changepoint regression methodology produces time-varying beta estimates for each fund-month observation, capturing how funds dynamically adjust their risk exposures in response to changing market conditions. Additionally, the data include fund characteristics: net asset value (NAV), fund age, management fees, and performance fees.

3.4 Proposed Measures

3.4.1 Risk Factor Timing Intensity (TSACT)

Our proposed measure, TSACT, quantifies the extent to which a fund's returns vary due to time-varying risk exposures rather than exposure to factor returns alone. Conceptually, TSACT captures dynamic repositioning behavior: funds that actively adjust their factor loadings over time will exhibit higher tracking error between their actual risk-adjusted returns and returns implied by assumed-constant exposures.

Formally, for each fund i at time t, we compute TSACT using a rolling 36-month window ending at time $t-1$ (lagged to avoid look-ahead bias). Let $\hat{\beta}_{i,t,k}$ denote fund i's estimated exposure to risk factor k at time t. Let $f_{k,t}$ denote the return on risk factor k at time t. The estimated return implied by time-varying exposures (excluding alpha) is:

$$\hat{r}_{i,t}^{TV} = \sum_{k=1}^{K} \hat{\beta}_{i,t,k} f_{k,t} \tag{3.1}$$

The estimated return implied by assumed-constant exposures uses the fund's average estimated beta over the 36-month window:

$$\hat{r}_{i,t}^{CONST} = \sum_{k=1}^{K} \bar{\hat{\beta}}_{i,k} f_{k,t} \tag{3.2}$$

where $\bar{\hat{\beta}}_{i,k} = \frac{1}{36} \sum_{\tau=t-36}^{t-1} \hat{\beta}_{i,\tau,k}$ is the average estimated exposure to factor k over the window.

TSACT is defined as the annualized standard deviation of the difference between these two return series:

$$\text{TSACT}_{i,t} = \sqrt{12} \times \text{SD}\left(\hat{r}_{i,\tau}^{TV} - \hat{r}_{i,\tau}^{CONST}\right), \quad \tau = t-36, \ldots, t-1 \tag{3.3}$$

Funds with higher TSACT exhibit greater divergence between time-varying and constant exposure returns, indicating more active repositioning. A fund maintaining stable exposures over the window will have TSACT near zero, while a fund that frequently adjusts exposures in response to information will have higher TSACT. Importantly, TSACT measures risk factor timing intensity orthogonal to the fund's average level of risk: two funds with identical average exposures but different dynamic behavior will have different TSACT values.

3.4.2 Distinctiveness Benchmarks

To assess whether mere distinctiveness from the hedge fund industry predicts returns, as proposed by Sun *et al.* (2012), we construct two benchmark measures. These measures capture correlation with aggregate hedge fund returns but do not measure risk factor timing intensity per se.

HFCORR measures the 36-month rolling correlation between fund i's excess returns and the NAV-weighted average excess return of all funds in the sample:

$$\text{HFCORR}_{i,t} = \text{Corr}\left(r_{i,\tau}, \bar{r}_{\tau}\right), \quad \tau = t-36, \ldots, t-1 \tag{3.4}$$

where $r_{i,\tau}$ is fund i's excess return and $\bar{r}_{\tau} = \sum_j w_{j,\tau} r_{j,\tau}$ is the NAV-weighted aggregate return with weights $w_{j,\tau} = \frac{\text{NAV}_{j,\tau}}{\sum_j \text{NAV}_{j,\tau}}$.

Funds with lower HFCORR exhibit return patterns less correlated with the industry average, potentially indicating distinctive investment strategies. Sun *et al.* (2012) argue that such distinctiveness signals superior information or skill, predicting higher returns.

HFBETA measures the sensitivity of fund i's returns to aggregate hedge fund returns, computed via rolling 36-month regression:

$$r_{i,\tau} = \hat{\alpha}_i + \widehat{\text{HFBETA}}_{i,t} \times \bar{r}_\tau + \epsilon_{i,\tau}, \quad \tau = t-36, \ldots, t-1 \tag{3.5}$$

HFBETA captures a fund's systematic exposure to industry-wide shocks. Funds with HFBETA far from one exhibit distinctive risk profiles, either loading less on common factors (HFBETA < 1) or amplifying industry movements (HFBETA > 1).

While HFCORR and HFBETA both measure distinctiveness, they capture different dimensions. HFCORR reflects linear association in returns, while HFBETA measures systematic exposure scaled by return volatility. Both serve as benchmarks against which to evaluate TSACT: if distinctiveness alone predicts returns, HFCORR and HFBETA should be significant predictors. In contrast, if active repositioning specifically predicts returns, TSACT should dominate these measures.

3.4.3 Descriptive Statistics

Table 3.1 presents descriptive statistics for selected measures and fund returns. The sample includes 53,847 fund-month observations after requiring 36 months of data to compute risk factor timing intensity and distinctive measures. TSACT exhibits substantial cross-sectional variation, with a median of 1.23% (annualized) and interquartile range from 0.57% to 2.50%.

HFCORR shows a median of 0.38, indicating that the typical fund's returns exhibit moderate positive correlation with aggregate hedge fund returns. The interquartile range spans 0.19 to 0.60, revealing substantial heterogeneity in how closely funds co-move with the industry. Some funds exhibit near-zero or negative correlation (minimum = -0.44), suggesting highly idiosyncratic strategies, while others are tightly linked to industry performance (maximum = 0.95).

HFBETA has a median of 0.32. The interquartile range of 0.09 to 0.79 indicates most funds load less than proportionally on aggregate hedge fund returns. This pattern is consistent with macro hedge funds maintaining diversified exposure across multiple asset classes rather than simply amplifying a common factor. The maximum HFBETA of 8.54 indicates some funds exhibit

very high sensitivity to industry movements, while the minimum of -1.61 suggests certain funds move inversely to the aggregate.

Return volatility (VOL) shows a median of 3.02% (annualized), with interquartile range from 1.38% to 5.91%. The median monthly excess return is 0.02%, with wide dispersion ranging from losses of -58.62% to substantial gains of 68.91%, reflecting the heterogeneous performance characteristic of hedge funds.

Table 3.1: Descriptive Statistics of Activeness Measures

Measure	Min	25th Pct	Median	75th Pct	Max
TSACT (%)	0.01	0.57	1.23	2.50	18.85
HFCORR	-0.44	0.19	0.38	0.60	0.95
HFBETA	-1.61	0.09	0.32	0.79	8.54
VOL (%)	0.06	1.38	3.02	5.91	83.79
RETURN (%)	-58.62	-0.40	0.02	0.51	68.91

Note: This table reports summary statistics - minimum, 25th percentile, median, 75th percentile and maximum - of TSACT, HFCORR, HFBETA, annualized volatility and annualized monthly returns across all macro hedge funds and months in our sample. TSACT is time-series risk factor timing intensity (annualized tracking error between time-varying and assumed-constant beta returns). HFCORR is correlation with aggregate hedge fund returns. HFBETA is the estimated beta with respect to aggregate hedge fund returns. VOL is return volatility (annualized standard deviation). RETURN is monthly excess return. TSACT, VOL, and RETURN are expressed in percentages. HFCORR and HFBETA are reported as coefficients. All measures are computed using lagged 36-month windows to avoid look-ahead bias. Sample includes 53,847 fund-month observations from 438 unique funds covering January 2009 to August 2024 (after requiring 36 months of data).

3.5 Cross-Sectional Regressions

3.5.1 Fama-MacBeth Methodology

We employ Fama-MacBeth cross-sectional regressions (Fama & MacBeth, 1973) to test whether risk factor timing intensity measures predict future fund returns. This methodology estimates cross-sectional regressions each month and computes time-series averages of the coefficients. Specifically, for each month t, we estimate:

$$r_{i,t} = \gamma_{0,t} + \gamma_{1,t} \times \text{TSACT}_{i,t-1} + \gamma_{2,t} \times \mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{3.6}$$

where $r_{i,t}$ is fund i's excess return in month t, $\text{TSACT}_{i,t-1}$ is lagged time-series risk factor timing intensity, and $\mathbf{X}_{i,t-1}$ includes additional lagged predictors

(HFCORR, HFBETA, volatility, factor loadings, fund characteristics). The one-month lag ensures that all right-hand side variables are observable to investors forming portfolios at the end of month $t-1$. The Fama-MacBeth coefficient on TSACT is $\hat{\gamma}_1 = \frac{1}{T}\sum_{t=1}^{T}\gamma_{1,t}$.

The Fama-MacBeth coefficients represent the predicted difference in annualized returns associated with changes in the explanatory variables. For TSACT, the coefficient of 0.88 indicates the estimated increase in annualized returns (in percentage points) for each one-unit increase in TSACT. Given that TSACT exhibits substantial cross-sectional variation (interquartile range from 0.57% to 2.50%), the estimated coefficient suggests economically meaningful relationships between risk factor timing intensity and fund performance.

3.5.2 Univariate Regressions

Table 3.2 reports univariate Fama-MacBeth regressions of monthly excess returns on TSACT, HFCORR and HFBETA separately. TSACT exhibits a positive and statistically significant coefficient of 0.88 (t-statistic = 2.16), indicating that funds with higher time-series risk factor timing intensity earn superior returns.

In contrast, the distinctiveness measures show weaker predictive power. HFCORR yields a coefficient of 0.01 (t-statistic = 0.68), and HFBETA produces a coefficient of 0.02 (t-statistic = 1.64). These results suggest that correlation or beta with respect to the aggregate hedge fund industry does not appear predict returns, contrary to the distinctiveness hypothesis of Sun *et al.* (2012). However, the divergence between our findings and theirs may reflect differences in market context (Brazil vs. US), fund strategies, or distinctiveness measurement (return correlation vs. style peer groups).

3.5.3 Multivariate Regressions

Table 3.3 presents multivariate Fama-MacBeth regressions controlling for multiple predictors. Column (4) includes all three risk factor timing intensity measures jointly. TSACT remains strongly significant with a coefficient of 1.11 (t-statistic = 3.05), actually increasing in magnitude relative to the univariate specification. This increase suggests that TSACT captures active repositioning orthogonal to industry correlation. HFCORR and HFBETA remain insignificant in this specification.

Column (5) adds control variables including fund volatility (VOL) and lagged factor loadings (BETA-BXMKT, BETA-USMKT, BETA-BXBOND5Y,

Table 3.2: Univariate Fama-MacBeth Regressions

Measure	Coefficient
TSACT	**0.8790**
	(**2.16**)
HFCORR	0.0113
	(0.68)
HFBETA	0.0162
	(1.64)

Notes: This table presents Fama-MacBeth regression coefficients (annualized) from univariate regressions of monthly fund returns on lagged risk factor timing intensity measures. All right-hand side variables are standardized within each month to have zero mean and unit standard deviation. T-statistics are computed from the time-series of monthly coefficients and adjusted for autocorrelation using Newey-West. Bold indicates |t-stat| > 1.96.

BETA-USBOND5Y). The inclusion of factor loadings is crucial: it addresses the concern that TSACT simply proxies for funds maintaining high average exposures to well-performing factors. If TSACT merely reflected persistent factor tilts rather than dynamic repositioning, controlling for average exposures should eliminate its significance. Instead, TSACT remains significant at 0.89 (t-statistic = 2.41), confirming that the predictive power stems from time-variation in exposures rather than their levels.

Column (6) presents the full specification including fund characteristics: NAV (log size), AGE, MGMT (management fee), and PFEE (performance fee). TSACT remains significant at 0.84 (t-statistic = 2.31), while NAV enters positively and significantly (coefficient = 0.0039, t-statistic = 4.82), indicating that larger funds earn higher returns after controlling for risk factor timing intensity. Management and performance fees both enter negatively and significantly, consistent with fees eroding net investor returns. The robustness of TSACT across these specifications provides strong evidence that time-series risk factor timing intensity predicts returns independent of size effects, fee structures, and factor exposures.

3.5.4 Extended Holding Periods

The monthly regression results suggests that TSACT helps predict one-month-ahead returns. However, investors in hedge funds face practical constraints on rapid rebalancing. Hedge funds typically impose redemption restrictions, with many funds requiring advance notice periods or imposing lock-ups. Consequently, investors cannot easily exploit one-month predictability

Table 3.3: Multivariate Fama-MacBeth Regressions

Variable	(1)	(2)	(3)	(4)	(5)	(6)
TSACT	**0.8790**			**1.1142**	**0.8895**	**0.8403**
	(**2.16**)			(**3.05**)	(**2.41**)	(**2.31**)
HFCORR		0.0113		0.0113	-0.0045	-0.0104
		(0.68)		(0.81)	(-0.34)	(-0.80)
HFBETA			0.0162	0.0007	0.0051	0.0010
			(1.64)	(0.06)	(0.43)	(0.09)
VOL					-0.0871	-0.0441
					(-0.37)	(-0.19)
BETA-BXMKT					-0.0511	-0.0365
					(-0.75)	(-0.53)
BETA-USMKT					0.0645	0.0529
					(1.00)	(0.82)
BETA-BXBOND5Y					-0.0299	-0.0239
					(-0.71)	(-0.57)
BETA-USBOND5Y					-0.0010	0.0063
					(-0.04)	(0.23)
NAV						**0.0039**
						(**4.82**)
AGE						0.0000
						(0.61)
MGMT						**-0.0088**
						(**-3.52**)
PFEE						**-0.0007**
						(**-3.75**)

Notes: This table presents Fama-MacBeth regression coefficients from cross-sectional regressions of monthly fund excess returns on lagged fund characteristics. TSACT is time-series risk factor timing intensity (tracking error between time-varying and constant beta returns). HFCORR is correlation with aggregate hedge fund returns. HFBETA is beta with respect to aggregate hedge fund returns. VOL is return volatility (annualized standard deviation). BETA-BXMKT, BETA-USMKT, BETA-BXBOND5Y, and BETA-USBOND5Y are lagged factor loadings for Brazilian equity, US equity, Brazilian 5-year bonds, and US 5-year bonds, respectively. NAV is the natural logarithm of fund assets under management. AGE is fund age in months. MGMT and PFEE are management and performance fees, respectively. All continuous variables are standardized within each month. T-statistics (in parentheses) are Newey-West adjusted. Bold indicates |t-stat| > 1.96.

through frequent trading. To assess whether TSACT remains predictive over more actionable horizons, Table 3.4 repeats the analysis using non-overlapping six-month periods. Returns are cumulated over each six-month interval, and risk factor timing intensity measures are computed using data from the six months prior to each period. This longer horizon reflects a more realistic investment timeline for hedge fund allocators.

The results demonstrate that TSACT's predictive power persists at extended horizons. In the univariate regression (Column 1), TSACT exhibits a coefficient of 1.07 with a t-statistic of 2.16, significant at the 5% level. The multivariate specification (Column 4) yields a coefficient of 1.56 with a t-statistic of 3.94, even stronger than the monthly equivalent and significant at the 1% level. The full specification with all controls (Column 6) produces a TSACT coefficient of 0.89 with a t-statistic of 2.81, maintaining statistical significance at the 1% level.

As in the monthly regressions, HFCORR and HFBETA remain insignificant across all specifications, while NAV, MGMT, and PFEE exhibit similar patterns. The consistency between monthly and six-month results demonstrates that the predictive power of TSACT is not limited to short horizons but extends to timeframes over which investors can realistically adjust their hedge fund allocations. This finding enhances the practical relevance of risk factor timing intensity as a fund selection criterion.

3.6 Portfolio Sorts

3.6.1 Univariate Sorts

As a complementary test, we construct equal-weighted quintile portfolios sorted on the lagged risk factor timing intensity and distinctiveness measures. At the end of each month, all funds are ranked on a given measure and allocated to one of five portfolios. Portfolios are rebalanced monthly, and returns are computed as the equal-weighted average across constituent funds. To assess risk-adjusted performance, we estimate four-factor alphas by regressing portfolio excess returns on BXMKT, USMKT, BXBOND5Y, and USBOND5Y.

Table 3.5 reports results for portfolios sorted on TSACT. The portfolio returns exhibit a positive spread, with Q5 earning 0.69% annualized alpha compared to 0.12% for Q1. However, the Q5-Q1 spread of 0.57% has a t-statistic of only 0.37, far from statistical significance. This lack of significance contrasts sharply with the Fama-MacBeth regression results, where TSACT

Table 3.4: Fama-MacBeth Regressions: Non-Overlapping 6-Month Periods

Variable	(1)	(2)	(3)	(4)	(5)	(6)
TSACT	**1.0650**			**1.5615**	**0.9761**	**0.8942**
	(**2.16**)			(**3.94**)	(**3.02**)	(**2.81**)
HFCORR		-0.0029		0.0115	-0.0001	-0.0056
		(-0.17)		(0.81)	(-0.01)	(-0.40)
HFBETA			0.0162	-0.0068	0.0020	-0.0004
			(1.35)	(-0.55)	(0.17)	(-0.03)
VOL					-0.0416	-0.0036
					(-0.14)	(-0.01)
BETA-BXMKT					-0.0342	-0.0233
					(-0.68)	(-0.46)
BETA-USMKT					0.1201	0.1011
					(1.13)	(0.98)
BETA-BXBOND5Y					-0.0243	-0.0187
					(-0.49)	(-0.38)
BETA-USBOND5Y					0.0150	0.0181
					(0.54)	(0.65)
NAV						**0.0033**
						(**3.87**)
AGE						-0.0000
						(-0.09)
MGMT						**-0.0115**
						(**-3.53**)
PFEE						**-0.0006**
						(**-2.57**)

Notes: This table presents Fama-MacBeth regression coefficients from cross-sectional regressions of fund excess returns over non-overlapping 6-month periods on lagged fund characteristics. Each calendar year is divided into two semesters: H1 (January-June) and H2 (July-December). For each fund-period, we compute the cumulative 6-month return and use fund characteristics measured at the start of the period. Cross-sectional regressions are run for each period, and coefficients are averaged across periods. TSACT is a measure of time-series risk factor timing intensity. HFCORR is the correlation between fund returns and aggregate hedge fund returns. HFBETA is the beta with respect to aggregate hedge fund returns. VOL is return volatility. BETA-BXMKT, BETA-USMKT, BETA-BXBOND5Y, and BETA-USBOND5Y are lagged factor loadings. NAV is the natural logarithm of fund assets under management. AGE is fund age in months. MGMT and PFEE are management and performance fees. T-statistics (in parentheses) are Newey-West adjusted. Bold indicates $|\text{t-stat}| > 1.96$.

significantly predicts returns.

Tables 3.6 and 3.7 present univariate sorts on the distinctiveness measures. HFCORR quintile portfolios show no monotonic pattern, with the Q5-Q1 spread producing an alpha of 0.28% with a t-statistic of 0.25. HFBETA portfolios exhibit a positive spread of 0.83% (t-statistic = 0.45), also insignificant. These results confirm that distinctiveness does not appear to predict returns in univariate sorts, consistent with the cross-sectional regression findings.

Table 3.5: Univariate Portfolio Sorts: TSACT

Quintile	Mean Return (%)	4-Factor Alpha (%)	Sharpe Ratio
Q1	0.0015 (1.01)	0.0012 (1.11)	0.288
Q2	0.0024 (0.74)	0.0003 (0.13)	0.202
Q3	0.0089 (1.55)	0.0035 (0.75)	0.408
Q4	0.0076 (0.84)	0.0030 (0.44)	0.231
Q5	0.0238 (1.12)	0.0069 (0.44)	0.303
Q5 - Q1	0.0223 (1.07)	0.0057 (0.37)	0.294

Notes: This table presents equal-weighted portfolio returns, four-factor alphas, and Sharpe ratios (annualized) for quintile portfolios sorted on TSACT. Portfolios are rebalanced monthly. 4-Factor alpha are computed by regressing excess returns on BXMKT, USMKT, BXBOND5Y, USBOND5Y. All standard errors are Newey-West adjusted. Bold indicates |t-stat| > 1.96.

3.6.2 Extended Holding Periods

We assess the timing intensity-return relationship over extended holding periods. Table 3.8 reports portfolio sorts with extended holding periods of 6 and 12 months. Rather than rebalancing monthly, funds are allocated to quintiles and held for the specified horizon, with portfolios overlapping to maintain full investment. The lack of outperformance of portfolios sorted on TSACT for longer extended periods also contrasts the Fama-MacBeth regression results.

3.6.3 Bivariate Sorts: TSACT and Volatility

The disconnect between Fama-MacBeth regressions and univariate portfolio sorts suggests that the timing intensity-return relationship operates

Table 3.6: Univariate Portfolio Sorts: HFCORR

Quintile	Mean Return (%)	4-Factor Alpha (%)	Sharpe Ratio
Q1	0.0064 (0.95)	0.0028 (0.46)	0.268
Q2	**0.0124** (**2.26**)	**0.0097** (**2.37**)	0.597
Q3	0.0048 (0.51)	0.0001 (0.01)	0.135
Q4	0.0062 (0.59)	-0.0035 (-0.42)	0.159
Q5	0.0142 (1.14)	0.0056 (0.59)	0.312
Q5 - Q1	0.0079 (0.65)	0.0028 (0.25)	0.180

Notes: This table presents equal-weighted portfolio returns, four-factor alphas, and Sharpe ratios (annualized) for quintile portfolios sorted on HFCORR. Portfolios are rebalanced monthly. 4-Factor alpha are computed by regressing excess returns on BXMKT, USMKT, BXBOND5Y, USBOND5Y. All standard errors are Newey-West adjusted. Bold indicates |t-stat| $>$ 1.96.

Table 3.7: Univariate Portfolio Sorts: HFBETA

Quintile	Mean Return (%)	4-Factor Alpha (%)	Sharpe Ratio
Q1	-0.0003 (-0.06)	-0.0011 (-0.24)	-0.016
Q2	0.0037 (1.17)	0.0020 (0.80)	0.307
Q3	0.0047 (1.00)	0.0008 (0.21)	0.268
Q4	0.0114 (1.53)	0.0061 (1.12)	0.406
Q5	0.0249 (1.08)	0.0072 (0.42)	0.289
Q5 - Q1	0.0251 (1.11)	0.0083 (0.45)	0.302

Notes: This table presents equal-weighted portfolio returns, four-factor alphas, and Sharpe ratios (annualized) for quintile portfolios sorted on HFBETA. Portfolios are rebalanced monthly. 4-Factor alpha are computed by regressing excess returns on BXMKT, USMKT, BXBOND5Y, USBOND5Y. All standard errors are Newey-West adjusted. Bold indicates |t-stat| $>$ 1.96.

Table 3.8: Univariate portfolio sorts on TSACT with extended holding period

Quintile	1-Month	6-Month	12-Month
Q1	0.0012	0.0010	0.0002
	(1.11)	(0.84)	(0.14)
Q2	0.0003	0.0038	0.0046
	(0.13)	(1.72)	(1.53)
Q3	0.0035	0.0058	0.0065
	(0.75)	(1.65)	(1.79)
Q4	0.0030	0.0102	0.0114
	(0.44)	(1.76)	(1.55)
Q5	0.0069	0.0062	0.0043
	(0.44)	(0.48)	(0.27)
Q5 - Q1	0.0057	0.0052	0.0041
	(0.37)	(0.39)	(0.25)

Notes: This table presents four-factor alphas (annualized, in percent) for portfolios sorted on TSACT with extended holding periods. Newey-West adjusted t-statistics. Bold indicates |t-stat| > 1.96.

through interactions with other fund characteristics rather than manifesting as a simple monotonic pattern. To investigate this hypothesis, we perform bivariate sorts conditioning TSACT on fund volatility. Since TSACT measures tracking error, it is naturally related to volatility: high-volatility funds may exhibit higher TSACT mechanically. However, the relevant economic question is whether, within funds with similar levels of volatility, those with higher TSACT earn superior returns.

We assign funds to three volatility groups (Low, Medium, High) based on their average volatility over the entire sample period. Within each volatility group, we sort funds into TSACT quintiles each month. This procedure controls for baseline risk profiles while isolating variation in dynamic repositioning behavior.

Table 3.9 presents four-factor alphas for the bivariate sorts. The results reveal striking heterogeneity. In the low-volatility group, high TSACT funds significantly underperform, with Q5 earning alpha of -0.44% (t-statistic = -1.63) and the Q5-Q1 spread producing alpha of -0.62% (t-statistic = -1.97). This negative relationship could reflect measurement error in the TSACT construct: when true fund volatility is low, estimation error in the time-varying risk factor exposures becomes relatively more important, adding noise to the TSACT measure. Since TSACT is computed as the tracking error between estimated time-varying and constant betas, funds with low baseline volatility are more susceptible to having their TSACT contaminated by beta estimation noise rather than reflecting genuine active repositioning. This interpretation is

consistent with a key limitation of exposure-based risk factor timing intensity measures.

In contrast, the medium-volatility group exhibits a strong positive relationship. The Q5-Q1 spread delivers alpha of 1.64% (t-statistic = 2.39), statistically significant at the 5% level. Within this group, Q5 funds earn alpha of 2.13% (t-statistic = 2.68), significantly positive.

The high-volatility group shows no clear pattern. The estimated Q5-Q1 spread alpha is large, 4.03% per year, but with a t-statistic of only 1.19, not significant at conventional levels. This heterogeneity across volatility groups may help explain why univariate sorts diverge from regression results: aggregating across volatility groups obscures offsetting effects, with TSACT predicting positive returns in medium-volatility funds but negative returns in low-volatility funds.

Table 3.9: Bivariate Sorts: Average Volatility Groups and TSACT

	TSACT Quintile					
Vol Group	Low	2	3	4	High	Q5-Q1
Low	0.0018	0.0015	0.0013	-0.0007	-0.0044	**-0.0062**
	(1.62)	(1.27)	(0.84)	(-0.39)	(-1.63)	(**-1.97**)
Medium	0.0049	0.0011	0.0053	0.0076	**0.0213**	**0.0164**
	(1.43)	(0.27)	(1.06)	(1.40)	(**2.68**)	(**2.39**)
High	-0.0005	-0.0182	-0.0067	-0.0008	0.0383	0.0403
	(-0.06)	(-1.17)	(-0.47)	(-0.04)	(1.10)	(1.19)

Notes: This table presents four-factor alphas (annualized, in percent) for portfolios sorted on TSACT within average volatility groups. Funds are assigned to volatility groups (Low, Medium, High) based on their average volatility across the entire sample period. Within each group, funds are sorted into TSACT quintiles each month. Portfolios are equal-weighted and rebalanced monthly. Newey-West standard errors. Bold indicates |t-stat| $>$ 1.96.

3.7 Conclusion

This essay investigates whether risk factor timing intensity predicts cross-sectional returns among Brazilian macro hedge funds. Adapting the active share concept to the hedge fund context, we construct TSACT, a measure quantifying the tracking error between returns implied by time-varying versus assumed-constant estimated factor exposures. Using daily data on 438 funds spanning January 2006 to August 2024, we test whether TSACT predicts future returns alongside distinctiveness benchmarks (HFCORR and HFBETA).

Fama-MacBeth cross-sectional regressions reveal that TSACT significantly predicts monthly excess returns, even after controlling for fund characteristics, factor loadings, and fees. This relationship strengthens in multivariate specifications and remains significant in non-overlapping six-month periods, demonstrating that time-series risk factor timing intensity captures meaningful information about future performance. In contrast, distinctiveness measures exhibit no predictive power, suggesting that low correlation with the aggregate hedge fund industry does not forecast returns in the Brazilian context.

However, univariate portfolio sorts on TSACT fail to generate significant alpha, revealing an apparent disconnect between regression and sorting evidence. Bivariate sorts conditioning on fund volatility partially resolve this puzzle. This heterogeneity potentially reflects varying signal-to-noise ratios in TSACT measurement: estimation error in time-varying betas may contaminate the risk factor timing intensity signal for low-volatility funds, while the signal remains clear for medium-volatility funds where true repositioning dominates measurement noise. This hypothesis merits further studies and is a potential extension of this research.

Conclusion

This dissertation investigates Brazilian macro hedge funds through three complementary perspectives, demonstrating that hedge fund positioning and behavior contain valuable information for inflation forecasting, systematic trading strategies, and fund selection. Chapter 1 establishes that macro hedge fund risk exposures can improve predictions of future inflation, with aggregate exposure to the BRL/USD exchange rate significantly forecasting cumulative inflation even after controlling for professional survey forecasts. Incorporating this positioning into forecasting models yields meaningful improvements. Chapter 2 demonstrates that hedge fund replication strategies benefit substantially from conditioning on cross-sectional dispersion in estimated exposures, with strategies that scale exposures inversely with dispersion achieving improved risk-adjusted returns and lower maximum drawdowns that persist after controlling for time-series momentum. Chapter 3 shows that fund-level risk factor timing intensity - proxied by tracking error between returns implied by time-varying versus assumed-constant exposures - significantly predicts cross-sectional returns in Fama-MacBeth regressions.

From a practical perspective, the dissertation's findings carry implications for multiple stakeholders. Policymakers and professional forecasters may benefit from incorporating hedge fund positioning into inflation forecasting frameworks. Market participants interested in hedge fund replication should consider conditioning strategies on cross-sectional dispersion in exposures, as this measure may contain information about signal quality and conviction. Investors allocating capital to hedge funds should focus not only on average risk exposures but also to the dynamic behavior of those exposures. More broadly, this dissertation demonstrates the value of high-quality hedge fund data for understanding market dynamics and extracting actionable signals.

Bibliography

Agarwal, Vikas, & Naik, Narayan Y. 2004. Risks and Portfolio Decisions Involving Hedge Funds. *The Review of Financial Studies*, **17**(1), 63–98.

Almeida, Caio, Fernandes, Marcelo, & Valente, Joao Paulo. 2021. Tail Risk Exposures of Hedge Funds: Evidence from Unique Brazilian Data. *Brazilian Review of Econometrics*, **41**(1), 151–175.

Amisano, Gianni, & Savona, Roberto. 2017. Mutual Funds Dynamics and Economic Predictors. *Journal of Financial Econometrics*, **15**(2), 302–330.

Andrews, Donald W. K., Lee, Inpyo, & Ploberger, Werner. 1996. Optimal change-point tests for normal linear regression. *Journal of Econometrics*, **70**(1), 9–38.

Ang, Andrew, Bekaert, Geert, & Wei, Min. 2007. Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better? *Journal of Monetary Economics*, **54**(4), 1163–1212.

Araujo, Gustavo Silva, & Gaglianone, Wagner Piazza. 2023. Machine Learning Methods for Inflation Forecasting in Brazil: New Contenders versus Classical Models. *Latin American Journal of Central Banking*, **4**(2), 100087.

Asness, Clifford, Krail, Robert, & Liew, John. 2001. Do Hedge Funds Hedge? *The Journal of Portfolio Management*, **28**(1), 6–19.

Atkeson, Andrew, & Ohanian, Lee E. 2001. Are Phillips Curves Useful for Forecasting Inflation? *Federal Reserve Bank of Minneapolis Quarterly Review*, **25**(1), 2–11.

Babu, Abhilash, Levine, Ari, Ooi, Yao Hua, Pedersen, Lasse Heje, & Stamelos, Erik. 2020. Trends Everywhere. *Journal of Investment Management*, **18**(1), 52–68.

Bali, Turan G., Brown, Stephen J., & Caglayan, Mustafa Onur. 2011. Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns? *Journal of Financial Economics*, **101**(1), 36–68.

Bali, Turan G., Brown, Stephen J., & Caglayan, Mustafa Onur. 2012. Systematic Risk and the Cross Section of Hedge Fund Returns. *Journal of Financial Economics*, **106**(1), 114–131.

Bali, Turan G., Brown, Stephen J., & Caglayan, Mustafa Onur. 2014. Macroeconomic Risk and Hedge Fund Returns. *Journal of Financial Economics*, **114**(1), 1–19.

Bali, Turan G., Brown, Stephen J., & Caglayan, Mustafa O. 2018. Upside Potential of Hedge Funds as a Predictor of Future Performance. *Journal of Financial and Quantitative Analysis*, **53**(3), 1243–1273.

Baltas, Nik, & Kosowski, Robert. 2013. Momentum Strategies in Futures Markets and Trend-Following Funds. *SSRN Electronic Journal*. Working paper; pre-print available on SSRN.

Billio, Monica, Getmansky, Mila, & Pelizzon, Loriana. 2012. Dynamic Risk Exposures in Hedge Funds. *Computational Statistics & Data Analysis*, **56**(11), 3517–3532.

Bollen, Nicolas P. B., & Whaley, Robert E. 2009. Hedge Fund Risk Dynamics: Implications for Performance Appraisal. *The Journal of Finance*, **64**(2), 985–1035.

Breiman, Leo. 2001. Random Forests. *Machine Learning*, **45**(1), 5–32.

Cao, Charles, Chen, Yong, Liang, Bing, & Lo, Andrew W. 2013. Can Hedge Funds Time Market Liquidity? *Journal of Financial Economics*, **109**(2), 493–516.

Capocci, Daniel, Corhay, Albert, & Hubner, Georges. 2005. Hedge Fund Performance and Persistence in Bull and Bear Markets. *The European Journal of Finance*, **11**(5), 361–392.

Chen, Yong, Han, Bing, & Pan, Jun. 2021. Sentiment Trading and Hedge Fund Returns. *The Journal of Finance*, **76**(4), 2001–2033.

Chen, Yu-Chin, Rogoff, Kenneth, & Rossi, Barbara. 2010. Can Exchange Rates Forecast Commodity Prices? *The Quarterly Journal of Economics*, **125**(3), 1145–1194.

Cremers, K. J. Martijn, & Petajisto, Antti. 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. *The Review of Financial Studies*, **22**(9), 3329–3365.

Cremers, K. J. Martijn, Fulkerson, Jon A., & Riley, Timothy B. 2019. Challenging the Conventional Wisdom on Active Management: A Review of the Past 20 Years of Academic Literature on Actively Managed Mutual Funds. *Financial Analysts Journal*, **75**(4), 8–35.

Cujean, Julien, & Hasler, Michael. 2017. Why Does Return Predictability Concentrate in Bad Times? *The Journal of Finance*, **72**(6), 2717–2758.

D'Agostino, Antonello, & Surico, Paolo. 2009. Does Global Liquidity Help to Forecast US Inflation? *Journal of Money, Credit and Banking*, **41**(2-3), 479–489.

D'Agostino, Antonello, McQuinn, Kieran, & O'Brien, Derry. 2012. Identifying the Best Forecasters: A Classification Problem. *Journal of Money, Credit and Banking*, **44**(5), 1013–1023.

Diebold, Francis X., & Mariano, Roberto S. 1995. Comparing Predictive Accuracy. *Journal of Business & Economic Statistics*, **13**(3), 253–263.

Duanmu, Jun, Malakhov, Alexey, & McCumber, William R. 2018. Beta Active Hedge Fund Management. *The Journal of Financial and Quantitative Analysis*, **53**(6), 2525–2558.

Duanmu, Jun, Li, Yongjia, & Malakhov, Alexey. 2020. Capturing Hedge Fund Risk Factor Exposures: Hedge Fund Return Replication with ETFs. *Financial Review*, **55**(3), 405–431.

Fama, Eugene F., & MacBeth, James D. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, **81**(3), 607–636.

Faust, Jon, & Wright, Jonathan H. 2013. Forecasting Inflation. *Pages 2–56 of:* Elliott, Graham, & Timmermann, Allan (eds), *Handbook of Economic Forecasting*, vol. 2. Elsevier.

Forni, Mario, Hallin, Marc, Lippi, Marco, & Reichlin, Lucrezia. 2003. Do Financial Variables Help Forecasting Inflation and Real Activity in the Euro Area? *Journal of Monetary Economics*, **50**(6), 1243–1255.

Fung, William, & Hsieh, David A. 1997. Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies*, **10**(2), 275–302.

Fung, William, & Hsieh, David A. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. *Review of Financial Studies*, **14**(2), 313–341.

Fung, William, & Hsieh, David A. 2004. Hedge Fund Benchmarks: A Risk Based Approach. *Financial Analysts Journal*, **60**(5), 65–80.

Fung, William, & Hsieh, David A. 2008. Hedge Fund Replication Strategies: Implications for Investors and Regulators. *Financial Analysts Journal*, **64**(2), 55–72.

Garcia, Márcio G. P., Medeiros, Marcelo C., & Vasconcelos, Gabriel F. R. 2017. Real-time Inflation Forecasting with High-dimensional Models: The Case of Brazil. *International Journal of Forecasting*, **33**(3), 679–693.

Goulding, Christian L., Harvey, Campbell R., & Mazzoleni, Michele G. 2023a. Breaking Bad Trends. *Financial Analysts Journal*, **80**(1), 84–98.

Goulding, Christian L., Harvey, Campbell R., & Mazzoleni, Michele G. 2023b. Momentum Turning Points. *Journal of Financial Economics*, **149**(3), 378–406.

Gregoriou, Greg N., & Duffy, Neal E. 2006. Hedge Funds: A summary of the literature. *Pensions*, **12**(1), 24–32.

Gregoriou, Greg N., Racicot, FranÃ§ois-Ã‰ric, & ThÃ©oret, Raymond. 2021. The Response of Hedge Fund Tail Risk to Macroeconomic Shocks: A Nonlinear VAR Approach. *Economic Modelling*, **94**, 843–872.

Hasanhodzic, Jasmina, & Lo, Andrew W. 2007. Can Hedge-Fund Returns Be Replicated?: The Linear Case. *Journal of Investment Management*, **5**(2), 5–45.

Hong, Harrison, & Yogo, Motohiro. 2012. What Does Futures Market Interest Tell Us about the Macroeconomy and Asset Prices? *Journal of Financial Economics*, **105**(3), 473–490.

Hong, Yueran, Jiang, Fuwei, Meng, Lu, & Xue, Bin. 2024. Forecasting Inflation Using Economic Narratives. *Journal of Business & Economic Statistics*, **43**(1), 216–231.

Hurst, Brian, Ooi, Yao Hua, & Pedersen, Lasse Heje. 2017. A Century of Evidence on Trend-Following Investing. *The Journal of Portfolio Management*, **44**(1), 15–29.

Hutchinson, Mark C., & O'Brien, John. 2020. Time Series Momentum and Macroeconomic Risk. *International Review of Financial Analysis*, **69**, 101469.

Joaquim, Gustavo P. G., & Moura, Marcelo L. 2011. Performance and Persistence of Brazilian Hedge Funds During the Financial Crisis. *Brazilian Review of Finance*, **9**(4), 525–548.

Jordão, Gustavo A., & Moura, Marcelo L. de. 2011. Performance Analysis of Brazilian Hedge Funds. *Journal of Multinational Financial Management*, **21**(3), 165–176.

Kat, Harry M., & Palaro, Helder P. 2007. Who Needs Hedge Funds? A Copula-Based Approach to Hedge Fund Return Replication. *Journal of Alternative Investments*, **10**(2), 80–93.

Kim, Abby Y., Tse, Yiuman, & Wald, John K. 2016. Time series momentum and volatility scaling. *Journal of Financial Markets*, **30**, 103–124.

Lambert, Marie, & Platania, Federico. 2020. The macroeconomic drivers in hedge fund beta management. *Economic Modelling*, **91**, 65–80.

Mamaysky, Harry, Spiegel, Matthew, & Zhang, Hong. 2008. Estimating the Dynamics of Mutual Fund Alphas and Betas. *The Review of Financial Studies*, **21**(1), 233–264.

Medeiros, Marcelo C., Vasconcelos, Gabriel F. R., & Freitas, Eduardo. 2016. Forecasting Brazilian Inflation with High-Dimensional Models. *Brazilian Review of Econometrics*, **36**(2), 223–254.

Medeiros, Marcelo C., Vasconcelos, Gabriel F. R., Veiga, ÃfÂlvaro, & Zilberman, Eduardo. 2021. Forecasting Inflation in a Data-Rich Environment: The Benefits of Machine Learning Methods. *Journal of Business & Economic Statistics*, **39**(1), 98–119.

Mincer, Jacob A., & Zarnowitz, Victor. 1969. The Evaluation of Economic Forecasts. *Pages 3–46 of:* Mincer, Jacob A. (ed), *Economic Forecasts and Expectations: Analysis of Forecasting Behavior and Performance*. National Bureau of Economic Research.

Moreira, Alan, & Muir, Tyler. 2017. Volatility-Managed Portfolios. *The Journal of Finance*, **72**(4), 1611–1644.

Moskowitz, Tobias J., Ooi, Yao Hua, & Pedersen, Lasse Heje. 2012. Time Series Momentum. *Journal of Financial Economics*, **104**(2), 228–250.

O'Doherty, Michael S., Savin, Neil E., & Tiwari, Ashish. 2017. Hedge Fund Replication: A Modelâ€Combination Approach. *Review of Finance*, **21**(4), 1767–1804.

Patton, Andrew J., & Ramadorai, Tarun. 2013. On the High-Frequency Dynamics of Hedge Fund Risk Exposures. *The Journal of Finance*, **68**(2), 597–635.

Petajisto, Antti. 2013. Active Share and the Three Pillars of Active Management: Skill, Conviction and Opportunity. *Financial Analysts Journal*, **69**(4), 40–54.

Racicot, François-Éric, & Théoret, Raymond. 2016. Macroeconomic shocks, forward-looking dynamics, and the behavior of hedge funds. *Journal of Banking & Finance*, **62**, 41–61.

Siegmann, Arjen, & Stefanova, Denitsa. 2017. The evolving beta–liquidity relationship of hedge funds. *Journal of Empirical Finance*, **44**, 286–303.

Stafylas, Dimitrios, & Andrikopoulos, Athanasios. 2020. Determinants of Hedge Fund Performance during 'Good' and 'Bad' Economic Periods. *Research in International Business and Finance*, **52**, 101130.

Stafylas, Dimitrios, Anderson, Keith, & Uddin, Moshfique. 2018. Hedge Fund Performance Attribution under Various Market Conditions. *International Review of Financial Analysis*, **56**, 221–237.

Stock, James H., & Watson, Mark W. 1999. Forecasting Inflation. *Journal of Monetary Economics*, **44**(2), 293–335.

Stock, James H., & Watson, Mark W. 2002. Forecasting Using Principal Components From a Large Number of Predictors. *Journal of the American Statistical Association*, **97**(460), 1167–1179.

Stock, James H., & Watson, Mark W. 2003. Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature*, **41**(3), 788–829.

Stock, James H., & Watson, Mark W. 2007. Why Has U.S. Inflation Become Harder to Forecast? *Journal of Money, Credit and Banking*, **39**(s1), 3–33.

Sun, Zheng, Wang, Ashley W., & Zheng, Lu. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. *The Review of Financial Studies*, **25**(1), 96–143.

Titman, Sheridan, & Tiu, Cristian. 2011. Do the Best Hedge Funds Hedge? *The Review of Financial Studies*, **24**(1), 123–168.

Zou, Hui. 2006. The Adaptive Lasso and Its Oracle Properties. *Journal of the American Statistical Association*, **101**(476), 1418–1429.