PONTIFÍCIA UNIVERSIDADE CATÓLICA
DO RIO DE JANEIRO

Manuela Mesquita de Magalhães

The dynamics of institutions beliefs and portfolio choices

Dissertação de Mestrado

Thesis presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Prof. Carlos Viana de Carvalho

Rio de Janeiro
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To my parents and to my whole village.

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Abstract

Mesquita de Magalhães, Manuela; Viana de Carvalho, Carlos (Advisor). **The dynamics of institutions beliefs and portfolio choices**. Rio de Janeiro, 2022. 45p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Empirical studies of how actions respond to expectations are of increasing relevance, as they provide vital information on agents' choices and contribute to theoretical models. We explore how this pass-through occurs in institutional investors in Brazil. We assemble a novel dataset by matching data on institutions' forecasts of inflation, the exchange rate and the interest rate with their hedge funds portfolio holdings. This dataset allows us to investigate how institutional investors' expectations are related to their portfolio choices. We document that increases in funds' inflation and exchange rate expectations are correlated with decreases in their exposures to fixed rate bonds. We also observe a negative correlation between their expectation of the interest rate and their exposure to inflation bonds once we control for the other variables.

Keywords

Expectations; Portfolio choice; Inflation expectations; Heterogeneous beliefs.

Resumo

Mesquita de Magalhães, Manuela; Viana de Carvalho, Carlos. **A dinâmica de expectativas e escolhas de portfolio de fundos de investimento**. Rio de Janeiro, 2022. 45p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Estudos empíricos de como ações respondem às expectativas são de crescente importância, pois fornecem informações essenciais sobre as escolhas dos agentes e contribuem para modelos teóricos. Nós construímos uma base de dados inédita combinando dados de previsões de investidores institucionais do valor mensal de variáveis macroeconômicas com suas escolhas de portfolio. Essa base nos permite investigar como esses dois aspectos estão correlacionados. Encontramos que um aumento de expectativa de inflação e da expectativa de câmbio estão correlacionados com uma redução na exposição a pré fixados. Também observamos uma correlação negativa entre as expectativas da taxa de juros e a exposição à inflação se controlamos para as expectativas das demais variáveis.

Palavras-chave

Expectativas; Escolha de portfolio; Expectativas de inflação; Expectativas heterogêneas.

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List of Abreviations

CVM –Securities and Exchange Commission of Brazil

BCB – *Brazil Central Bank*

"[l]ove of kindness, without a love to learn, finds itself obscured by foolishness. Love of knowledge, without a love to learn, finds itself obscured by loose speculation. Love of honesty, without a love to learn, finds itself obscured by harmful candour. Love of straightforwardness, without a love to learn, finds itself obscured by misdirected judgment. Love of daring, without a love to learn, finds itself obscured by insubordination. And love for strength of character, without a love to learn, finds itself obscured by intractability."

Confucius, *The Analects, trans. William Edward Soothill (New York: Dover, 1995), 107. In On China, Henry Kissinger..*

"Cantar, e cantar, e cantar
A beleza de ser um eterno aprendiz"

Luiz Gonzaga do Nascimento Júnior, *O que é, o que é?.*

1
Introduction

Recently, we have observed an increasing relevance of empirical studies on how actions respond to expectations and on expectations themselves. That is intimately linked with the fact that models with deviations from the Rational Expectation Hypothesis (REH) have become increasingly popular.

Data on belief formation and dynamics then becomes essential to inform the belief formation processes in alternative models. Expectations reported on data do not seem to be simply noise, as opposed to what became a common view after the rational expectations revolution.

Expectation data can also help distinguish between different theories. Monika Piazzesi and Salomao (2009), for instance, are able to explain several features of movements in bond premia. They do so by accounting for the actual expectation structure over the last century, while previous literature focused on time varying risk aversion. There is also a large strand of literature focusing on heterogeneous expectations and market structure to explain common empirical puzzles in finance. Survey data combined with portfolio data is a valuable input there, as it allows us to check whether agents do behave as these theories propose.

Institutional investors' are an important part of the market, as they are responsible for high volumes of trading. That is why we seek to document how their expectations are related to their portfolio choices. We first show that even among sophisticated investors there is considerable disagreement and alternating degrees of optimism. We proceed to build a novel dataset matching investors' forecasts of macroeconomic variables and their portfolio holdings. We look at their predictions of the current month inflation, exchange rate and interest rate (when it is a month in which the Central Bank announces the interest rate benchmark). Since we do not observe the forecasts and the portfolio holdings at the same time, we estimate the latter through a state space asset class factor model. Our results reveal a negative correlation between investors' inflation and exchange rate expectations and their exposures to fixed rate bonds. We also observe a negative correlation between their expectation of the interest rate and their exposure to inflation-linked bonds once we control for the other variables.

1.1 Related literature

We contribute to a literature that investigates empirically the association between expectations and actions. Giglio et al. (2021) has a similar goal as ours but in a different setting. They investigate retail investors' expectations and investment choices, as well as the dynamic of their belief formation. Greenwood and Shleifer (2014) show that expectations are correlated between different surveys and with mutual fund flows. Gennaioli, Ma, and Shleifer (2016) show that CFO's expectations of earnings growth have a high predictive power of both corporate investment plans and actual investment, even if compared to traditional measures, such as Tobin's Q. Our paper contributes by investigating a different set of agents, institutional investors, and their portfolio choices. To our knowledge, we are the first to investigate such a setting.

We also seek to contribute to a literature connecting investors' expectations and market structure to explain common economic features of financial markets. Part of this literature explores disagreements and changes in beliefs among market participants (Hong and Stein (2007), Harrison and Kreps (1978), Scheinkman and Xiong (2003)). Some use survey data to model different belief formation process. Examples are Gennaioli and Shleifer (2018) and Bhandari, Borovicka, and Ho (2019).

We also contribute to the wide literature that documents disagreements in macroeconomic expectations in various groups of agents, in special to the literature documenting disagreements among experts. There is extensive evidence of such disagreements and their persistence, such as Mankiw, Reis, and Wolfers (2004), Coibion and Gorodnichenko (2012), Dovern, Fritsche, and Slacalek (2012) and Andrade and Le Bihan (2013). Andre et al. (2021) reports heterogeneous subjective models of the economy among both households and experts. Giacomini, Skreta, and Turen (2020) documents persistent disagreement between professional forecasters.

Using the data of the same survey we use, the FOCUS survey, Gaglianone et al. (2019) documents that investors respond to incentives. This finding informs part of our methodology, as will be described in section 2.1. Another paper that uses FOCUS survey data is Gaglianone, Issler, and Matos (2016), where they show professional forecasts systematically underpredict inflation. Carvalho and Minella (2009) documents that the common forecast error prevails over the idiosyncratic component for the survey participants. We are the first to document another phenomena in the data, though, of dynamic disagreement among institutions.

2
Data

We use two main sources of data to construct our panel linking beliefs and portfolio choices, namely the Focus Survey from Brazil Central Bank (BCB) and data on portfolio holdings and funds' performances from the Comissão de Valores Mobiliários (CVM), which is the Brazilian institution equivalent to the Securities and Exchange Commission of the United States.

2.1
Data on expectations

We use public expectations data from the FOCUS survey. The FOCUS survey is a survey of professional forecasters conducted by the Central Bank of Brazil. The most common concerns regarding the use of survey data to measure expectations do not seem to apply here. These concerns are that agents do not know precisely how to state expectations and that agents do not have incentives to report their true expectations. They do not apply here for two reasons. First, agents surveyed are professional forecasters and are certainly well aware of the meaning of the variables they are predicting. Second, they have incentives to declare their true predictions - BCB publishes every month a report announcing who were the "Top 5" predictors for each variable, defined by the five predictors with the least average error over the last 6 months. Indeed, Gaglianone et al. (2019) shows that institutions improve both the extensive and intensive margin of prediction on the days when the predictions are valid for the contest - they not only publish more forecasts but also more accurate ones.

Gaglianone, Issler, and Matos (2016) interpret that institutions who do not update often their forecasts outside of the critical dates have not changed their prediction. But it could also be that those institutions do not attach much value to updating their forecasts outside of critical dates, even if their internal predictions have changed, since they would not accrue any particular benefit from that. The contest has a few participation requirements relating to updating forecasts outside of critical dates, but they can be met by, for example, updating a yearly prediction - which does not count to the top 5 ranking - each month. Therefore, it seems that using forecasts outside of critical dates could affect the validity of our panel analysis.

Hence, in the present version of this paper, we focus on forecasts valid on critical dates, which amount to, at most, two forecasts of each variable per month per institution. For the interest rate and the exchange rate there are two critical dates while for the other variables there is only one. The forecasts are of the current month value of the variable (so called nowcasts). Inflation and exchange rate predictions are available every month. Interest rate predictions are available only in the months where there are announcements of the interest rate benchmark made by the Central Bank.

The microdata is anonymized and made public at the BCB webpage with a lag of one year[1]. It is a panel, so each institution has a identifier code, and it is not disclosed to which institution each identifier code corresponds. To retrieve institutions' identifiers, we use the contest promoted by the BCB. Each month, for each variable, BCB assigns to each institution a score related to their past recent errors and the frequency of their forecast updates, and makes public the institutions with the five lowest scores and their scores. We simulate the contest and match institutions scores for each variable in each month with the ones in the microdata. There is considerable variability in the ranking, so we are able to identify 89 out of the 147 institutions present in the data, who are responsible for 92,7% of the forecasts present in the data from November 2001 to April 2020. That is equivalent to 3,236,001 forecasts, when we count all variables and out of critical dates forecasts.

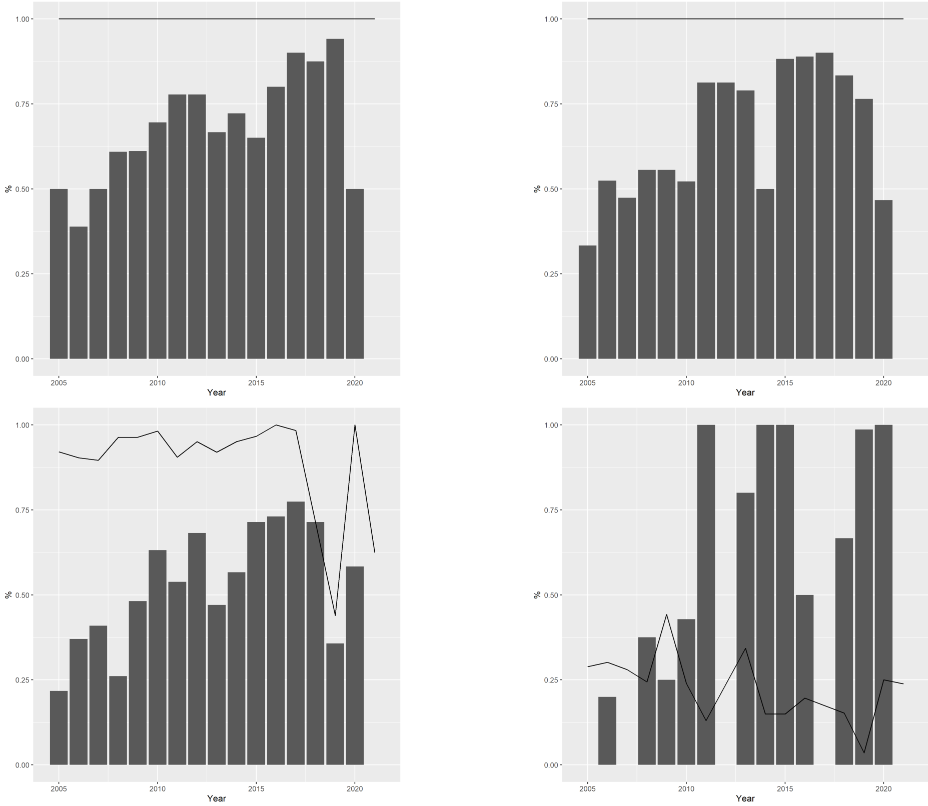
Not all institutions allow their data to be published. There are 102 institutions that appear in the top 5 rankings at least once and that we are not able to match with the ids in the data. Although it is a large number, it is mostly driven by institutions that ceased to exist before the microdata was made available - and therefore the authorization required. Figure 2.1 shows in bars the percentage of the institutions present in the top 5 ranking that were matched to the microdata.

One difficulty arises due to the existence of ties in the contest. If two or more institutions have the same score in a given month, we cannot identify the id of those institutions using only this information, as there will be more than one possibility for the match. Therefore, we exclude ties from our algorithm. The line in figure 2.1 corresponds to the share of positions that were not ties each year. Ties are not present in the inflation measures rankings, but occur quite often in the interest rate ranking and sometimes in the exchange rate ranking[2].

1. We commit to mantain the anonymity of the data and not disclose the identified institutions' identifier codes.

2. For a tie to happen, it is not sufficient that two institutions have the same prediction

Figure 2.1: Quality of the matching algorithm over time



Clockwise, the variables are, from the top left: inflation measured by IPCA, inflation measured by IGPM, the interest rate and the exchange rate.

Among the identified institutions, there are 42 asset managers companies, 24 banks, 9 consultancy firms, 7 investment management companies and 7 others (pension funds and insurance companies). Of those, we will only investigate asset managers, because we want to investigate the relationship between portfolio choices and expectations and they are the only group we could obtain this information. We then select for each institution hedge funds focused on macroeconomic conditions.

2.2 Data on portfolio holdings

CVM requires hedge funds to disclose their portfolio holdings once a month. They can ask for confidentiality regarding certain assets holdings, but that confidentiality can only last up to three months. Since we use data until 2020, this is not a problem for our analysis.

We select for each institution identified in the data a hedge fund focused in macroeconomic conditions. These funds are active traders seeking to profit from changes and imbalances in macroeconomic conditions. They invest in

in one month, it is necessary that they hold the same prediction for several months in a row.

bonds, equities, foreign currencies and other assets. Because of that, they are called multi-market funds. Although they may differ in their velocity and style of trading, they have the common goal of finding opportunities to profit based on correctly assessing the macroeconomic scenario.

However, the problem we face is that portfolio holdings data do not usually refer to the same date as the critical date for the expectations. For instance, the critical date for the IPCA measure for inflation is, in most of our sample, around the middle of the month, while the portfolio holdings data usually refers to the last day of each month. Since the hedge funds we are interested in trade in high frequency, simply comparing those holdings with the institution expectations would probably mislead us in our conclusions.

That is why we estimate an asset class factor model, as described in chapter 3. For this estimation, we use the daily value of hedge funds' assets and the daily returns of indexes correlated to the macroeconomic variables of our interest. The data on funds' value comes from CVM, while the data on the data on the indexes is available at the Bloomberg terminal.

2.3 Disagreements in the inflation market

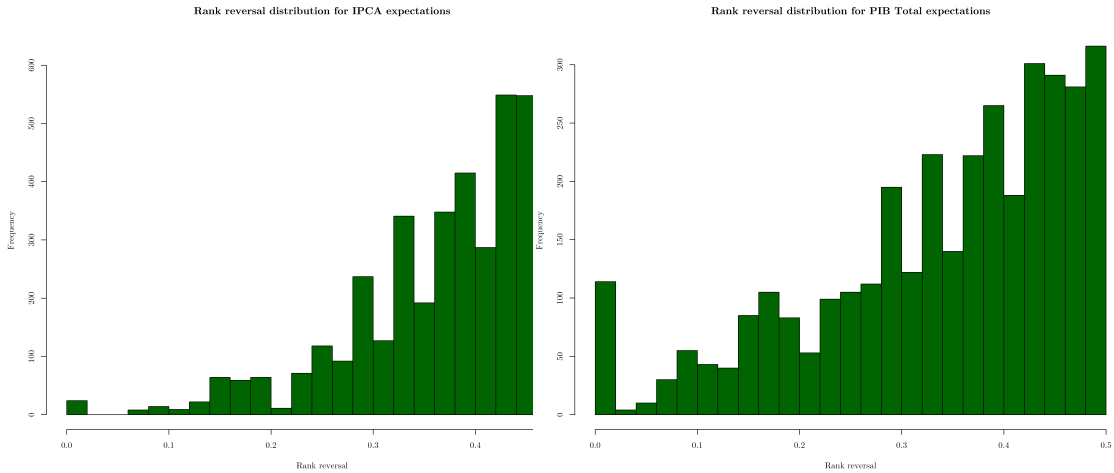
Whether our estimation can succeed depends on the extent to which there is heterogeneity in firms' forecasts. The institutions we are studying are highly sophisticated, therefore, it is natural for one to wonder whether we will be able to properly retrieve a relation between firms' forecasts and their portfolio choices. One way to assess this heterogeneity is the one used by Giglio et al. (2021), where they regress individual expectations against time series fixed effects. Here, as expected, as our agents are professional forecasters and not retail investors, time series effects account for much more of the changes in expectations, varying from 78 to 98% depending on the variable. However, that should not be taken at face value - even small disagreements could be enough for professional investors to trade. Many costs that retail investors face are hardly prohibitive for them, such as attention costs.

Hence, I adopt a different measure of disagreement here, one that correlates with the fixed effects but better elucidates the behavior of the institutions. Borrowing from the IO literature, I construct the rank reversal statistic proposed by Chandra and Tappata (2011), but with different variables and meaning here. It is constructed as follows: let $\mathbf{s}_{i,j}(y_\tau)$ be a vector of the difference between the expectations of variable y τ periods ahead, of two institutions i, j over $T_{i,j}$ days, such that $E_{i,t}(y_\tau) \geq E_{j,t}(y_\tau)$ is observed most of the time. The rank reversal between institutions i and j is defined as the share of observations in which $E_{j,t}(y_\tau) > E_{i,t}(y_\tau)$:

$$r_{i,j} = \frac{1}{T_{i,j}} \sum_{t=1}^{T_{i,j}} \mathbb{I}_{[E_{j,t}(y_\tau) > E_{i,t}(y_\tau)]}$$

It is a measure of dynamic disagreement, so that we see if there is room for continuous trade between the funds. In figure 2.2 I plot this statistic for monthly inflation and GDP quarterly growth nowcasts ($\tau = 0$) valid on the critical dates, for institutions that have both valid forecasts at the same period at least 5 times.

Figure 2.2: Distribution of rank reversals for inflation (IPCA) and GDP Growth nowcasts



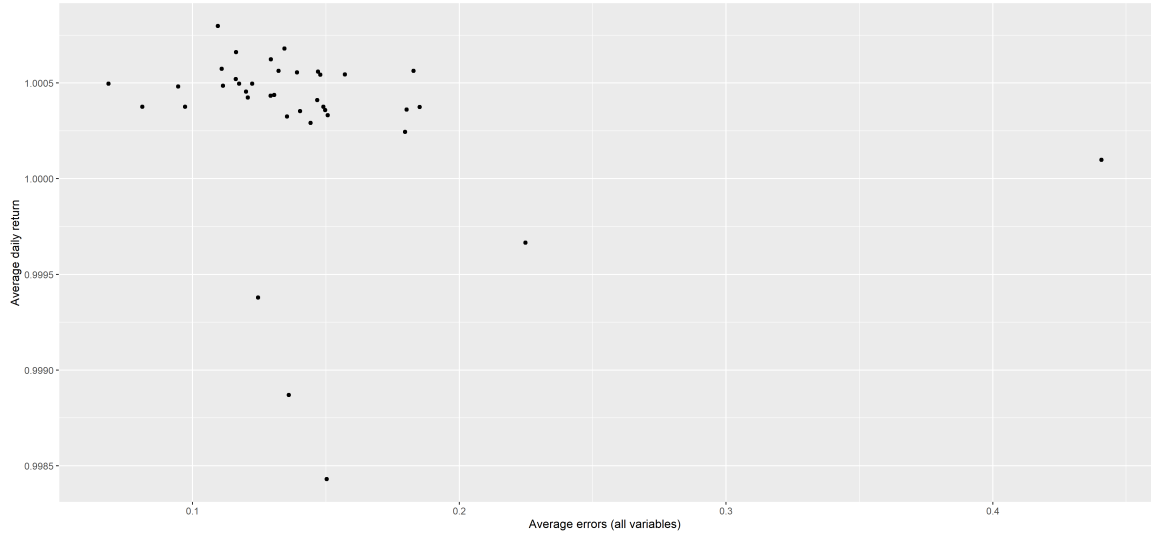
As figure 2.2 shows, there is considerable disagreement and change in institutions' relative position when it comes to monthly inflation and GDP quarterly data. In appendix A, we show that this finding is robust to a different inflation measurement index. We also show that there is way less temporal variation in the ranking of the exchange rate and the Selic interest rate, which is in part because many institutions hold exactly the same predictions.

2.4 Returns and errors

A first natural enquiry into whether hedge funds portfolio choices are correlated to their portfolio holdings is to see if their returns are correlated with the accuracy of their predictions. In figure 2.4, we plot the average returns and average prediction error of the IPCA measure of inflation for of the hedge funds we are studying. In table 2.1, I plot the coefficient of the following regression

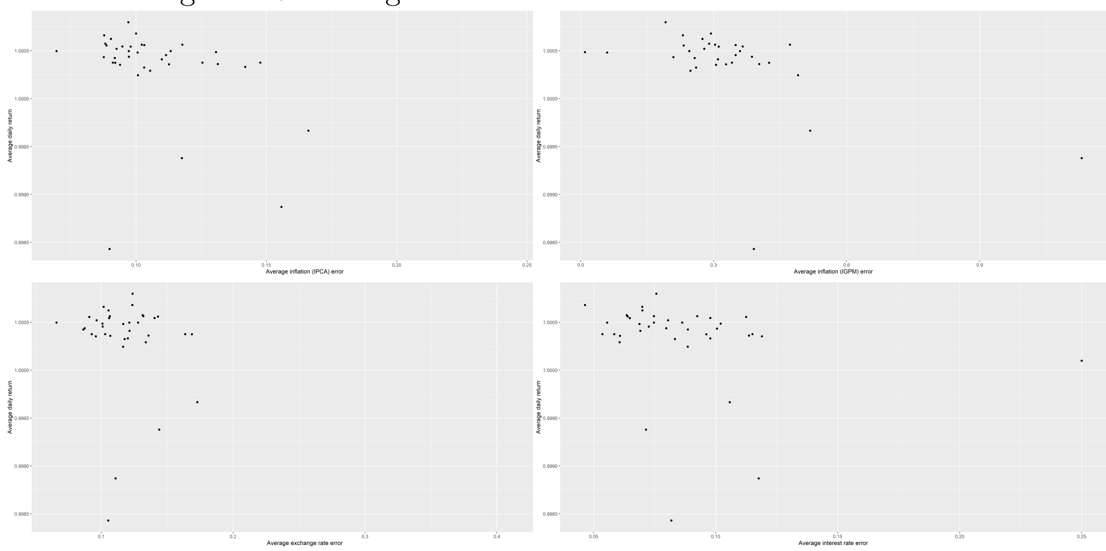
$$\bar{r}_j = \beta \overline{\text{error}(i)}_j + \epsilon_j \tag{2-1}$$

Figure 2.4: Average returns and errors of all variables together



for each variable $i \in$ {inflation, exchange rate, interest rate)} where $\bar{r}_j$ is the average return of fund j and $\overline{\text{error}(i)}_j$ is the average expectation error of variable i by fund j. The sign of every correlation is negative, as one would expect. Inflation errors seem to be the ones most related to the funds' performance.

Figure 2.3: Average returns and errors for each variable



Clockwise, from the top left: inflation measured by IPCA, inflation measured by IGPM, the interest rate and the exchange rate.

Table 2.1: Value and significance of the coefficient relating the error of each variable to funds' returns

Inflation (IPCA)	Inflation (IGPM)	Interest rate	Exchange rate	All variables
-0.004154*	-0.001242***	-0.002914	-0.000940	-0.001516

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3
First stage estimation

3.1
Asset class factor models

Sharpe (1992) first proposes the use of an asset class factor model to decompose mutual funds performance between selection and style, in what has been know now return based style analysis, or just style analysis. The crucial equation behind asset class factor models is

$$\tilde{R}_{i,t} = \beta_{i,1}\widetilde{F}_{1,t} + \beta_{i,2}\widetilde{F}_{2,t} + \ldots + \beta_{i,n}\widetilde{F}_{N,t} + \widetilde{\varepsilon}_{i,t} \tag{3-1}$$

where there are N asset classes, $\tilde{R}_{i,t}$ is the return of hedge fund i in t, $\widetilde{F}_{1,t}$ is the excess return of asset class i in t, $\beta_{i,j}$ is the exposure of institution i to asset class j and $\widetilde{\varepsilon}_{i,t}$ account for selection and for the imperfections of the asset class to fully represent the returns. The asset classes should be mutually exclusive, exhaustive and have returns that are not collinear.

The implementation of the return based style analysis will usually consider a window of time in which the exposures to the asset classes are supposed to be roughly constant. However, the hedge funds we are studying have a quite dynamic portfolio management. Pizzinga and Fernandes (2006) propose a solution to this problem: using state space models and estimating them using the Kalman filter. They then model the exposures as a Gaussian random walk, for two reasons: parsimony and simplicity, and acommodation of exposures that change fundamentally over time. We follow this specification, and we construct three different state space models to better deal with the heterogeneity of hedge funds. For reference, the transition equation for all models is 3-2 and the observation measurement is 3-3.

$$x_{j,t+1} = x_{j,t} + Bu_{t,j}, u_{t,j} \sim NID(0, \sigma^2_{1,j}) \tag{3-2}$$

$$y_{j,t} = C_t x_{j,t} + D\epsilon_t, \epsilon_{t,j} \sim NID(0, \sigma^2_{2,j}) \tag{3-3}$$

All models have the same transition equation and state vector. The state vectors are given by

$$x'_{j,t} = \begin{bmatrix} \alpha_j & s_{j,t}(1) & \ldots & s_{j,t}(N) \end{bmatrix} \tag{3-4}$$

where α_j is a constant accounting for the funds costs and the selection of assets, and $s_{j,t}(n)$ is fund j exposure to asset class $n \in N$ in t. Let $\mathbf{I}_Z$ be an identity matrix of dimension ZxZ. There are N gaussian independent errors in the transition equation, one for each asset class. Therefore, matrix B is defined as

$$B = \begin{bmatrix} \mathbf{0}_{1xN} \\ \mathbf{I}_N \end{bmatrix} \tag{3-5}$$

Our simplest model considers only the returns of both the hedge funds and the asset classes. Let $r_{j,t}$ be the excess return of fund j in t and $\boldsymbol{\psi}'_t = \begin{bmatrix} \psi_{1,t} & \psi_{2,t} & \dots & \psi_{N,t} \end{bmatrix}$ be the vector containing the excess return $\psi_{n,t}$ of each asset class $n \in N$ in t. Then, in the simple model, $y_{j,t} = r_{j,t}$, $C_t = \begin{bmatrix} 1 & \boldsymbol{\psi}'_t \end{bmatrix}$ and $D = 1$.

We also want to be able to use the direct information we have on hedge funds' portfolio holdings once a month. Corrêa Fonseca (2020) does so by adapting the measurement equation. We do the same and we construct two different models, here named complex model and steep model. They differ in that the complex model combines data on both asset classes returns and portfolio holdings when portfolio holdings are observed, while the steep model ignores the information on returns when portfolio holdings are observed. In the next section, we detail how we calculate the exposure to each asset class from portfolio holdings. Since our measurement is imperfect, we include a measurement error relating the observed exposures to the actual exposures.

As mentioned, for both models, the transition equation is the same, but the measurement equations differ. Let $\mathbb{1}_{obs}(t)$ be an indicator function that assumes value 1 if the exposure is observed in t and 0 otherwise[1], and $\boldsymbol{\lambda}_{j,t} = [\ \lambda(1)_{j,t} \ \ \lambda(2)_{j,t} \ \ \dots \ \ \lambda(N)_{j,t}\ ]'$ a vector where $\lambda(n)_{j,t}$ is the observed exposure of hedge fund j to asset class n in t if it is observed and 0 otherwise.

Then, in the complex model,

$$y_{j,t} = \begin{bmatrix} r_{j,t} \\ \boldsymbol{\lambda}_{j,t} \end{bmatrix} \tag{3-6}$$

$$C_t = \begin{bmatrix} 1 & \boldsymbol{\psi}'_t \\ \mathbf{0}_{Nx1} & \mathbf{I}_N \mathbb{1}_{obs}(t) \end{bmatrix} \tag{3-7}$$

and

$$D = \begin{bmatrix} 1 & \mathbf{0}_{1xN} \\ \mathbf{0}_{Nx1} & \mathbf{I}_N(1 - \mathbb{1}_{obs}(t)) \end{bmatrix} \tag{3-8}$$

In the steep model,

1. Since the dates the exposures are observed are the same for all hedge funds, $\mathbb{1}_{obs}(t)$ is a function of t only.

$$y_{j,t} = \begin{bmatrix} (1 - \mathbb{1}_{obs}(t))r_{j,t} \\ \boldsymbol{\lambda}_{j,t} \end{bmatrix} \tag{3-9}$$

$$C_t = \begin{bmatrix} (1 - \mathbb{1}_{obs}(t)) \cdot \begin{bmatrix} 1 & \boldsymbol{\psi}'_t \end{bmatrix} \\ \mathbf{0}_{Nx1} & \mathbf{I}_N \mathbb{1}_{obs}(t) \end{bmatrix} \tag{3-10}$$

and

$$D = \begin{bmatrix} \mathbb{1}_{obs}(t) & \mathbf{0}_{1xN} \\ \mathbf{0}_{Nx1} & \mathbf{I}_N(1 - \mathbb{1}_{obs}(t)) \end{bmatrix} \tag{3-11}$$

We then estimate by maximum likelihood using the Kalman filter the variance of the errors for each model for each hedge fund, allowing different errors for each hedge fund and each equation, but imposing independence between them. After that, we estimate the states- the exposures - through the Kalman smoother.

3.2 Asset classes and directly observed exposures

There exists already some papers that apply asset class factor models to study Brazilian funds. See Maestri and Malaquias (2016) for a review of them and the chosen asset factors. A difference between us and most of them is that we do not include an index to represent gains related to bonds indexed to the Selic rate, which is an overnight rate (usually CDI or IMA-S), because we use the CDI as our risk free benchmark to calculate the excess returns of the funds and asset classes. Like most of them, we use Ibovespa to represent the Brazilian equity market and IRF-M to represent fixed rate bonds. For inflation, we use IMA-B, which tracks public bonds indexed to inflation measured by the IPCA, the same index we observe expectations. Lastly, for the exchange rate we use generic first brazilian currency.

Table 3.2 summarizes which index represent each asset class and how we calculate each asset class direct exposure from the portfolio holdings data.

Table 3.1: Asset classes and respective indexes and assets

Asset class	Representative index	Direct exposure assets
Inflation	IMAB index	NTN-B and DAP futures
Exchange rate	Generic first brazilian future currency	USD futures
Equity	Ibovespa index	Domestic equities
Fixed rate	IRFM	LTN and NTN-F

To see how the mapping from the data to the calculated exposures is done and its potential limits, I show below an example. The portfolio data of a certain fund in a certain month is displayed in table 3.2. A large part of its holdings is in investment in other funds. In this case, these funds are managed by the same firm. Regardless of that, we always consider the assets to which the funds are indirect exposed to, through the funds they invest in. There are a few reasons for that. First, there are cases such as this one where the fund is actually composed by other funds from the same firm. Second, funds may choose which asset classes they want to be exposed to at each moment through investing in other funds. Third, when we estimate our asset class factor model, we are inevitably including the indirect exposures. Therefore, it is incompatible with not including them in the calculated exposures.

We include indirect exposures of all degrees, that is, if fund A invests in fund B which, in turn, invests in fund C, the assets held by fund C will be included in the exposures of fund A. For instance, if fund C has 30% of exposure to inflation, if fund B holds 10% of its networth in fund C and fund A holds 50% of its networth in fund B, an exposure of 1.5% to inflation is included in fund A's direct exposures.

Table 3.2: Portfolio holdings of a fund

Asset	**Final position**			
	Quantity	**Value**		**% Net worth**
		Cost	**Market value**	
Investment in other funds	19.048.376		36.752.780,65	70,181
Investment in other funds	3.083.705		7.949.007,23	15,179
Investment in other funds	1.375.185		7.667.706,45	14,642
Investment in other funds	445.487		740.269,75	1,414
Cash			5.000,00	0,01
Accounts payable			746.389,38	-1,425
Accounts receivable			177,02	0

Here, there are 3 direct assets and 382 indirect ones. The way they are distributed in our asset classes is shown in table 3.3. Table 3.4 shows what are the assets that we are not including in any of our asset classes. Table 3.5 shows what are the assets that we are including in each asset class.

	Fixed rate	Selic	Other	Inflation	Equity
Number	2.00	29.00	238.00	2.00	114.00
Share of net worth	0.02	0.59	0.27	0.00	0.12

Table 3.3: Number and share of each asset class

Type of asset	Share	Type of public bond, Type of investment
Others	-0.03	-, Accounts payable
Others	0.01	-, Accounts receivable
Others	0.00	-, Accounts receivable on forward sales
Others	0.00	-, Cash
Share certificate	0.00	-, Certificate of deposits
Convertible debenture	0.00	-, Debentures
Simple debenture	0.00	-, Debentures
Subscription receipt	0.00	-, Equities and other securities on loan
Bond on external debt	0.00	-, Investments abroad
Others	0.03	-, Investments abroad
Call option	0.00	-, Long option
Put option	0.00	-, Long option
Others	0.01	-, Others
SWAP	-0.00	-, Payable SWAP differential
Public bonds	0.08	-, Public bonds
Public bonds	0.01	NTN-A3, Public bonds
Public bonds	0.00	NTN-C, Public bonds
SWAP	0.01	-, Receivable SWAP differential
Public bonds	0.02	-, Repurchase agreements
Call option	-0.00	-, Short option
Put option	-0.00	-, Short option
Financial letter	0.13	-, Term deposits and other tax free bonds

Table 3.4: Assets that do not belong to our asset classes

3.3 Performance of the estimates

To evaluate how well the estimated exposures do on predicting the variance of the quota value, we regress for each hedge the actual daily quota returns on the predicted quota returns (equation 3-12) and compute the R^2. It is the traditional fit measure used on the style analysis literature.

$$r_{j,t} = \alpha + \hat{r}_{j,t} + \epsilon_{t,j} \tag{3-12}$$

Table 3.6 shows the distribution of the computed R^2 across the three models.

Generally, the simple model does better than the other two. That is probably due to the way we calculate the exposures, as it restricts them to certain assets and do not include indirect exposures to each asset class through other assets. For 97.4 % of the funds, the simple model indeed does better, while for 2.6 % the complex model does better and for 0 % the steep model does better.

In appendix B, we show that the estimation works well for funds related to each of the chosen asset classes and in appendix C we display statistics about the estimated parameters for the errors. Figure 3.1 shows in the left side how

Asset class	Type of asset	Share	Type of public bond, Type of investment
Equity	Common stock	0.10	-, Equities
Equity	Preferred stock	0.02	-, Equities
Equity	Common stock	0.01	-, Equities and other securities on loan
Equity	Preferred stock	0.00	-, Equities and other securities on loan
Equity	Common stock	-0.00	-, Obligations due to loaned equities and other securities
Equity	Preferred stock	-0.00	-, Obligations due to loaned equities and other securities
Selic	Public bonds	0.59	LFT, Public bonds
Fixed rate	Public bonds	0.02	LTN, Public bonds
Inflation	Public bonds	0.00	NTN-B, Public bonds

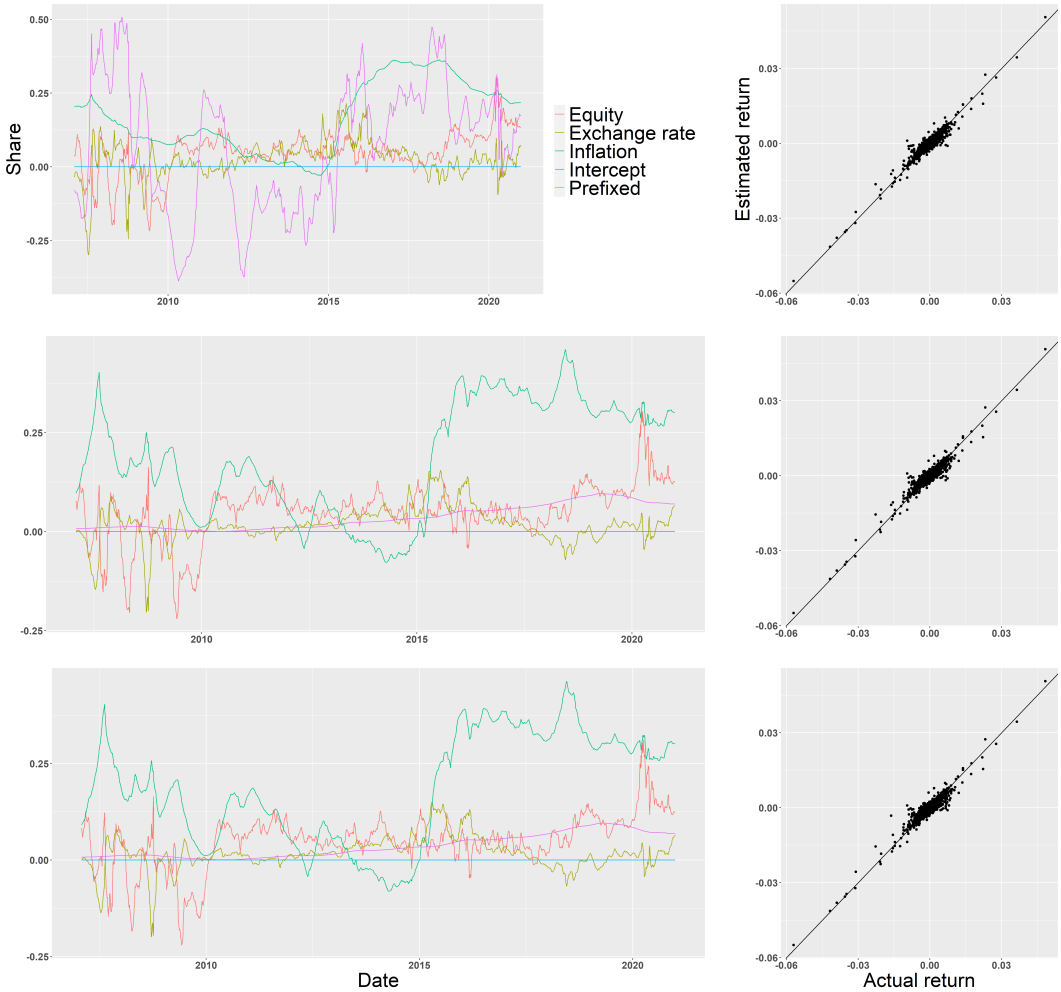
Table 3.5: Assets in our asset classes

Table 3.6: Summary statistics of R^2 across models

Statistic	N	Mean	St. Dev.	Min	Max
Simple model	39	0.742	0.197	0.091	0.969
Complex model	39	0.642	0.233	0.044	0.990
Steep model	39	0.503	0.287	0.0004	0.963

the calculated exposures vary over time for the fund portrayed on section 3.2 for each of the models. In the right side, figure 3.1 plots the actual returns of the fund and the ones implied by the estimation by each model and a 45º degree line for comparison. The actual and estimated returns are concentrated around the identity line in all models. We see a rise in the inflation share over time for all models and the main difference seem to be in the equity share, which is brought to near zero in the portfolio models and varies a lot in the simple model. The plots of the complex and the steep model are very similar, but not equal.

Figure 3.1: A fund estimated exposures and returns



From top to bottom: simple model, complex model and steep model.

4
Results

Our results are based in regressions with institution and date fixed effects. For all asset classes $n \in N$ and current month expectations variables $i \in I = \{\text{inflation, interest rate, exchange rate}\}$, we run

$$\hat{s}_{t,j}(n) = \alpha_t + \gamma_j + \beta \mathbb{E}_{t,j}(\text{var}_i) + \epsilon_{t,j} \tag{4-1}$$

where $\hat{s}(n)_{t,j}$ is the estimated exposure of hedge fund j to asset class n in t. To see how the expectations for other variables might affect the results, we also run

$$\hat{s}_{t,j}(n) = \alpha_t + \gamma_j + \beta \mathbb{E}_{t,j}(\text{var}_i) + \sum_{k \neq i} \beta_k \tilde{\mathbb{E}}_{t,j}(\text{var}_k) + \epsilon_{t,j} \tag{4-2}$$

where $\tilde{\mathbb{E}}_{t,j}(\text{var}_k)$ is the most recent valid expectation of variable k in t for hedge fund j.

It is important to acknowledge that one of our variables, $\hat{s}_{j,t}(n)$, is the result of the estimation process described in chapter 3. Therefore, it contains a measurement error, that is, $\hat{s}_{j,t}(n) = s_{j,t}(n) + \varepsilon_{t,j}$. But because it is our dependent variable, as long as $E(\varepsilon_{i,t}|\alpha_t, \gamma_j) = 0$ and $\mathbb{E}(\epsilon_{t,j}\varepsilon_{i,t}|\alpha_t, \gamma_j) = 0$, our estimates will be unbiased and the calculated standard errors will be the correct ones under the usual assumptions.

4.1
Inflation, exchange rate and interest rate

The results for the inflation expectation are displayed in tables 4.1 and 4.2. We find a positive and statistically significant relation between the expectation and the exposure to inflation assets, as it would be expected, but no statistical significant relation to the other asset classes. However, once we control for the most recent expectations for the other two variables, the only significant correlation the negative one with the exposure to fixed rate bonds. That might indicate that exposure to inflation indexed bonds increases when the economic conditions are such that expectations for inflation, interest rate and exchange rate are changing together. But when we see an isolated increase in the inflation expectation, what responds mostly, and with a high coefficient, is the exposure to fixed rate bonds.

Table 4.1: Correlation between exposures and ipca expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
IPCA expectation	-0.0218	0.0284	0.0925**	-0.2527
	(0.0481)	(0.0573)	(0.0445)	(0.1503)
Fixed-effects				
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,966	3,966	3,966	3,966
R^2	0.75325	0.49522	0.43247	0.42669
Within R^2	0.00044	0.00074	0.00259	0.00087

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4.2: Correlation between exposures and ipca expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
IPCA expectation	-0.0119	0.0148	0.0431	-0.5586***
	(0.0452)	(0.0494)	(0.0277)	(0.1672)
Fixed-effects				
Proxy for other variables expectation	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,660	3,660	3,660	3,660
R^2	0.77588	0.51491	0.41796	0.44872
Within R^2	0.00380	0.00095	0.00268	0.00919

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

One might argue that it makes little sense to try to associate exposure to inflation as we measure it to monthly nowcasts of inflation. In appendix E, we show variants of the same regression of table 4.2 looking at different time horizons of the inflation prediction: current year annual inflation, next year annual inflation, and the monthly inflation of 12 months ahead. These time horizons predictions are not included in the FOCUS contest and are therefore subject to the criticism we mentioned in section 2.1. To select the forecasts for the regression, we take the last valid forecast for the institution in the critical date of the inflation forecasts. The results do not change much from the ones considering inflation monthly nowcasts. All time horizons display the negative correlation to fixed rate bonds we find here, but it is only statistically significant for the next year annual inflation prediction.

Table 4.3 shows the correlation between exchange rate expectation and the exposure to each asset class. There is a strong negative and statistically significant correlation between its expectation and the exposure to fixed rate bonds. The same occurs when we control for the expectations of the other variables, as shown in table D.1 in appendix D.

Table 4.3: Correlation between exposures and exchange rate expectation

Dependent Variables: Model:	Equity (1)	Exchange rate (2)	Inflation (3)	Fixed rate (4)
Variables				
Exchange rate expectation	0.0219 (0.0221)	-0.0275 (0.0393)	-0.0222 (0.0309)	-0.3744** (0.1809)
Fixed-effects				
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	6,383	6,383	6,383	6,383
R^2	0.78295	0.50340	0.49077	0.51568
Within R^2	0.00057	0.00093	0.00019	0.00289

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

When it comes to the expectation for the interest rate, we find no statistically significant correlations when we do not control for the expectations for the other variables, as shown in table 4.4. It is important to note, though, that we do not have bonds indexed to the Selic rate as an asset class, so we cannot observe if the exposure to those rise as the expectation of the rate rises.

However, when we control for the expectations of other variables, we see a negative and statistically significant correlation to inflation exposure. Although we are controlling for the most recent expectation for inflation, it is the expectation only of the current month's inflation. Therefore, it could be that, conditional on the current inflation expectation, rises in the expectation of the interest rate are related to beliefs that inflation might be lower in the future, hence decreasing the funds' exposure to inflation in the moment. This explanation, however, conflicts with the regressions on appendix E for inflation horizons until the following year, mentioned above. Two main possibilities arise: one, that this relationship exists for longer horizons, which remains to be checked in the expectations data; two, that the fact that those expectations are not the critical ones is biasing the results.

Table 4.4: Correlation between exposures and selic expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
Selic expectation	-0.0145	0.0078	-0.0245	-0.0107
	(0.0088)	(0.0149)	(0.0211)	(0.1065)
Fixed-effects				
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	4,153	4,153	4,153	4,153
R^2	0.76233	0.48703	0.41947	0.42266
Within R^2	0.00048	0.00015	0.00047	4.68×10^{-6}

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4.5: Correlation between exposures and selic expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
Selic expectation	-0.0018	0.0094	-0.0520**	0.0297
	(0.0112)	(0.0151)	(0.0239)	(0.1031)
Fixed-effects				
Proxy for other variables expectation	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,833	3,833	3,833	3,833
R^2	0.77737	0.49862	0.40126	0.43699
Within R^2	0.00609	0.00098	0.00510	0.00238

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5
Conclusions

How investor's expectation's actually affect their choices is an important question. Hedge funds are responsible for a large share of capital markets and the way their investment choices respond to their forecasts can have important implications for policy. Here, we do a first attempt towards answering that question, in the context of hedge funds in Brazil.

The construction of a novel dataset comes with challenges that we have seeked to address in this work. The most relevant one is certainly the impossibility of observing direct portfolio holdings and forecasts in the same dates. Our solution to that was to estimate an asset class factor model to obtain the portfolio exposures in the same dates that we have the forecasts, what comes at a cost of efficiency.

Given those caveats, our results still are useful to shed light on hedge funds preferences and behavior. To our knowledge, we are the first to do so. There are three main results. First, that hedge funds inflation expectations is negatively correlated to their exposures to fixed rate bonds. Second, there is a strong and negative correlation between the exposure to fixed rate bonds and the exchange rate expectation, regardless of whether we control for the expectation of other variables. Third, we do not see statistically significant correlations between the expectation of the interest rate and the exposures to the chosen asset classes if we do not control for other variables expectations. If we control for them, though, we see a negative correlation with inflation exposure, what might indicate that agents expect inflation to fall in the future when they expect the interest rate to be higher, conditional on their current inflation expectation. Further research is required to investigate how this may change over time, as it may depend on hedge funds perception of the overall economy.

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A
Rank reversals

Figure A.1: Distribution of rank reversals for IGPM inflation measure

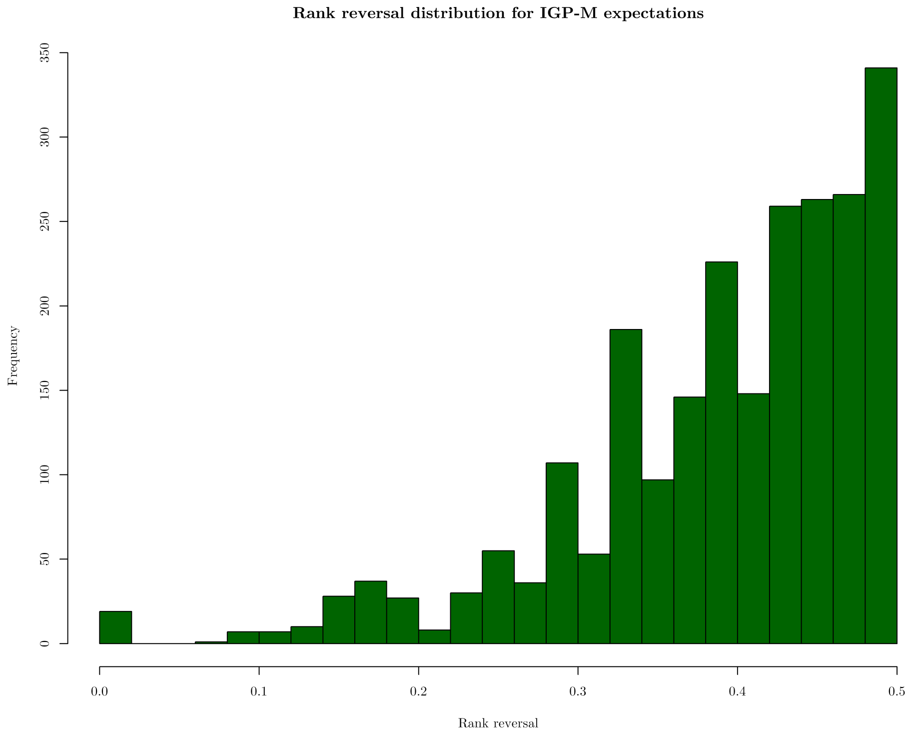
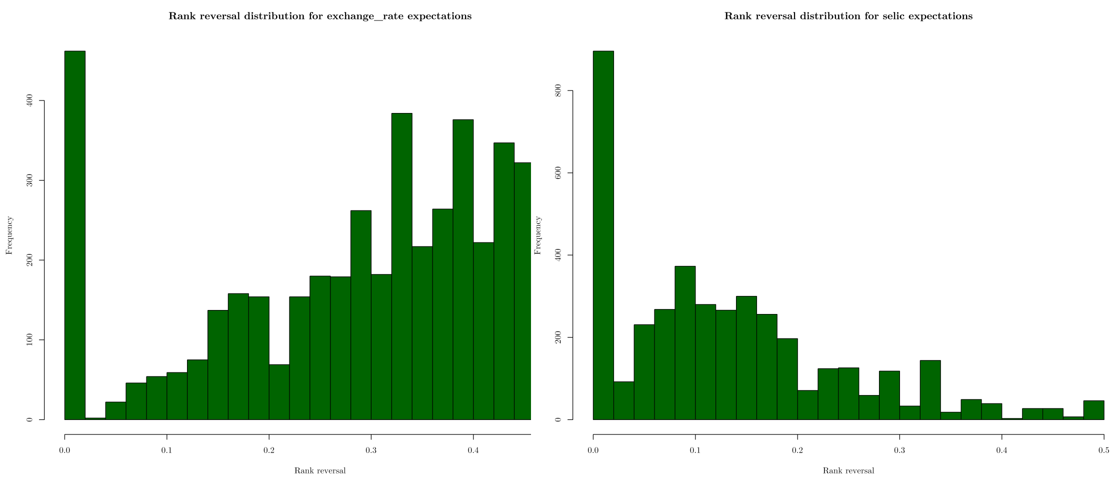


Figure A.2: Distribution of rank reversals for interest rate and exchange rate



B
Index funds

To check how well our models are working, we estimate them to four funds focused on each of the asset classes we use and a fund focused on Selic indexed bonds. Table B.1 displays the R^2 for them for each model and tables B.2 to B.6 display the summary stats of the exposures of each fund to the respective asset class. The models seem to be working well for those funds.

Table B.1: Summary statistics of R^2 across models

Statistic	N	Mean	St. Dev.	Min	Max
Simple model	5	0.903	0.159	0.624	0.997
Complex model	5	0.903	0.169	0.605	0.997
Steep model	5	0.871	0.237	0.449	0.998

Table B.2: Estimated exposures of a fund focused on Exchange Rate

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	3,839	−0.00000	0.000	−0.00000	−0.00000	−0.00000	−0.00000
Exchange rate	3,839	0.858	0.203	−0.240	0.771	0.986	1.500
Inflation	3,839	0.002	0.074	−0.195	−0.048	0.030	0.207
Fixed rate	3,839	0.079	0.090	−0.029	0.011	0.124	0.413

Table B.3: Estimated exposures of a fund focused on Ibov

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	1,709	0.947	0.088	−0.011	0.906	1.000	1.281
Exchange rate	1,709	−0.008	0.013	−0.022	−0.017	0.001	0.019
Inflation	1,709	0.073	0.054	0.027	0.034	0.111	0.180
Fixed rate	1,709	−0.095	0.065	−0.212	−0.140	−0.037	−0.011

Table B.4: Estimated exposures of a fund focused on IRFM

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	3,695	−0.0004	0.002	−0.007	−0.002	0.001	0.005
Exchange rate	3,695	0.00000	0.00000	−0.00000	−0.00000	0.00000	0.00000
Inflation	3,695	0.019	0.044	−0.119	−0.008	0.042	0.231
Fixed rate	3,695	0.752	0.274	−1.061	0.522	0.979	2.029

Table B.5: Estimated exposures of a fund focused on IMAB

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	1,968	−0.000	0.000	−0.00000	−0.000	0.000	0.000
Exchange rate	1,968	0.00000	0.00000	−0.00000	0.00000	0.00000	0.00000
Inflation	1,968	0.958	0.106	−0.252	0.921	1.016	1.406
Fixed rate	1,968	0.006	0.024	−0.077	−0.009	0.020	0.085

Table B.6: Estimated exposures of a fund focused on Selic

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	1,003	−0.001	0.002	−0.018	−0.001	0.0003	0.004
Exchange rate	1,003	0.0002	0.0002	−0.0001	0.00001	0.0004	0.0004
Inflation	1,003	0.004	0.002	−0.0001	0.002	0.006	0.007
Fixed rate	1,003	0.007	0.024	−0.028	−0.005	0.010	0.098

C
Estimated parameters

C.1
Transition

Table C.1: Distribution of estimated transition errors simple estimation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	39	−0.002	0.018	−0.028	−0.015	0.010	0.066
Exchange rate	39	0.012	0.019	−0.038	−0.001	0.021	0.066
Inflation	39	0.027	0.050	−0.014	−0.001	0.047	0.245
Fixed rate	39	0.131	0.116	−0.00000	0.051	0.174	0.418

Table C.2: Distribution of estimated transition errors complex estimation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	39	−0.003	0.019	−0.037	−0.016	0.006	0.047
Exchange rate	39	−0.002	0.010	−0.045	−0.00001	0.00000	0.017
Inflation	39	0.040	0.050	−0.021	−0.004	0.076	0.158
Fixed rate	39	0.026	0.040	−0.014	0.0003	0.031	0.131

Table C.3: Distribution of estimated transition errors steep estimation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Equity	39	0.025	0.051	−0.050	−0.013	0.100	0.100
Exchange rate	39	0.031	0.045	−0.011	−0.00000	0.100	0.100
Inflation	39	0.061	0.051	−0.020	0.015	0.100	0.167
Fixed rate	39	0.044	0.046	−0.015	0.006	0.100	0.118

C.2
Measurement

Table C.4: Distribution of estimated measurement error and intercept simple estimation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Intercept	39	0.00001	0.0001	−0.0005	−0.00004	0.0001	0.0005
Returns error	39	0.002	0.003	−0.002	0.0004	0.002	0.015

Table C.5: Distribution of estimated measurement errors and intercept complex estimation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Intercept	39	0.00002	0.0001	−0.001	−0.00003	0.0001	0.0004
Returns error	39	0.002	0.003	−0.002	0.001	0.003	0.015
Equity	39	0.123	0.096	−0.00004	0.054	0.156	0.393
Exchange rate	39	0.022	0.040	−0.002	−0.0001	0.028	0.137
Inflation	39	0.204	0.119	−0.00000	0.135	0.277	0.547
Fixed rate	39	0.183	0.167	−0.002	0.071	0.201	0.669

Table C.6: Distribution of estimated measurement errors and intercept steep estimation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Intercept	39	−0.000	0.000	−0	0	0	0
Returns error	39	0.029	0.045	−0.002	0.001	0.100	0.100
Equity	39	0.111	0.080	−0.007	0.066	0.144	0.320
Exchange rate	39	0.044	0.049	−0.003	−0.00000	0.100	0.131
Inflation	39	0.162	0.095	−0.017	0.100	0.234	0.380
Fixed rate	39	0.133	0.121	−0.006	0.086	0.141	0.626

D
Robustness

Table D.1: Correlation between exposures and exchange rate expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
Exchange rate expectation	0.0221	-0.0286	-0.0217	-0.3705**
	(0.0224)	(0.0396)	(0.0316)	(0.1793)
Fixed-effects				
Proxy for other variables expectation	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	6,344	6,344	6,344	6,344
R^2	0.78343	0.50686	0.49441	0.51929
Within R^2	0.00080	0.00183	0.00295	0.00497

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

E
Regressions using other time horizons for inflation

Table E.1: Correlation between exposures and current year inflation expectation

Dependent Variables: Model:	Equity (1)	Exchange rate (2)	Inflation (3)	Fixed rate (4)
Variables				
Current year inflation expectation	0.0083	-0.0219	0.0303	-0.1204
	(0.0102)	(0.0160)	(0.0339)	(0.0824)
Fixed-effects				
Proxy for other variables expectation	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,590	3,590	3,590	3,590
R^2	0.77727	0.51795	0.42260	0.44896
Within R^2	0.00581	0.00548	0.00771	0.01019

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table E.2: Correlation between exposures and next year inflation expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
Next year inflation expectation	0.0080	-0.0091	0.0094	-0.2301**
	(0.0069)	(0.0127)	(0.0110)	(0.0942)
Fixed-effects				
Proxy for other variables expectation	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,389	3,389	3,389	3,389
R^2	0.78627	0.52012	0.43423	0.47226
Within R^2	0.00620	0.00342	0.00576	0.03237

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table E.3: Correlation between exposures and 12 months ahead inflation expectation

Dependent Variables:	Equity	Exchange rate	Inflation	Fixed rate
Model:	(1)	(2)	(3)	(4)
Variables				
12 months ahead inflation expectation	0.0406	-0.0560	0.0182	-0.2680
	(0.0245)	(0.0415)	(0.0204)	(0.1993)
Fixed-effects				
Proxy for other variables expectation	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,485	2,485	2,485	2,485
R^2	0.83680	0.52901	0.54238	0.48172
Within R^2	0.00265	0.00719	0.00621	0.01174

Clustered (Institution) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*