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Man versus Machine: the performance of quantitative hedge funds in Brazil

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Introduction

Human beings are narrow sighted. We do not have the ability to clearly assess past, understand out role in the present and project future undertakes. By the time an individual is placed in a position of control, his/hers understanding of current developments define future results. In the hedge fund industry, which in deeply dependent on precise decision making, human sentiment is prone to play a significant part in outcomes.

Algorithmic trading in quantitative funds contrast with regular hedge fund practices. Trading activity that relies on automated systems for decision making is a growing practice, with major impact on financial culture (Hansen, 2020). Software design that is able to correct human-induced error certainly comes in hand while striving for rational risk assessment. After all, risk aversion is the primal instinct of microeconomic behavior, and to take sentiment out of that equation could drive interesting results.

A performance comparison between human and algorithmic trading within hedge funds is proposed in the Brazilian industry. However, to stress the hypothesis of human action, a crisis period framework is proposed. Using a diff-in-diff strategy, sentiment induced human intervention can be correctly isolated for research purposes. After all, in the Brazilian hedge fund industry, do humans stand a chance against algorithmic trading?

Research Problem and Objective

The goal of this study is to provide a performance comparison between quantitative hedge funds, in which managers program a strategy executed without human intervention, and traditional hedge funds, managed and operated by professionals aided by data analytics tools and software.

Investigations within the subject has been developed with mixed results. Striving to shed new light on the discussion, this paper proposes the following question: do quantitative funds perform better than traditional funds in crisis periods in Brazil? The underlying doubt within this question has behavioral roots, as sentiment driven bias affect decision-making processes of traditional funds and could affect performance.

Ramiah et al. (2015) reviews financial theory pathway through neoclassical and behavioral lenses, arguing that noise traders perform a pivotal role in financial markets. Behavioral bias and market anomalies can no longer be overseen by financial analysis and protocols that try to diminish their impacts on asset management should be investigated.

Chincarini (2014) e Manru e Yucan (2018) provide evidence of superior performance by quantitative investment funds compared to traditional funds. Chincarini (2014) developed a global database with data from 1970 to 2009 and reported that quantitative funds present better performance in crisis periods. The paper cites non-biased market timing within trading codes, or the absence of panic induced selling as main reasons for that phenomenon.

On the other hand, Khandani and Lo (2011) found different results by simulating market making activity during the event formally known as 2007's Quant Meltdown: a week of unprecedent losses for highly successful market neutral quantitative hedge funds. The paper found that liquidity shortage within this asset class, created by a "crowded trade" phenomenon, resulted in severe losses.

A puzzling factor during that particular week of August in the New York Stock Exchange (NYSE) is that there was no sign of market turmoil outside quantitative hedge funds. The evidence found by Khandani and Lo (2011) suggest the result of a highly correlated asset class with common behavior patterns, highly induced systemic risk and reinforce the argument of superiority in traditional human managed hedge funds.

After the “quant meltdown”, research on algorithm trading made great advances by questioning the impact on market efficiency. A seminal evidence published by Hendershott et al (2011) is that algorithm trading does improve market liquidity and lowers the cost of information. However, these finding had a historical perspective and did not consider possible setbacks that could surface with the technological access of new players.

Research on the informational impact of algorithmic trading shows that the practice does augment the price efficiency of information while reducing available information to which price responds (Weller, 2016). Syamala and Wadhwa (2020) found that algorithmic trading has positive results and increases market efficiency. Similar results are found by Hilbert and Darmon (2020): growing algorithmic trading increases price predictability (micro-level) while increases market uncertainty (macro-level). These contradictory results are a glimpse into the informational theory paradigm of machine learning: are there infinite levels of uncertainty?

Research on algorithmic trading tend to focus on market impact, informational costs and efficiency. Few studies access the impact of non-human trading on hedge fund performance. A diff-in-diff strategy is designed to assess the impact of algorithm strategy. Crisis periods act as an exogenous market shock.

Theoretical Framework

Economic decision making’s main dogma is perfect rationality. Agents maximize their utility by rationally weighting every single option available. This line of thought produced a range of elegant and precise models. The economy turned out to be somewhat explainable. Ironically, by opting for this "rational road", economists simultaneously opt for a bounded rationality model: economist are not optimizing their model. They are only *satisfacing,* a grammatical joint venture between satisfy and suffice.

The concept of *satisfacing* was firstly proposed by Herbert Simon (1955). It assumes that the decisions taken are not the best options, but they are good enough. It's a much more honest model. It is not as elegant nor as precise as the normative models of rationality, but it has a twist to it: it's psychologically realistic. By itself, *satisfacing* behavior could be enough to hypothesize in favor of algorithmic trader’s performance.

However, as observed in the endowment effect (Thaler, 1980), the role of sentiment in risk analysis (Slovic, Finucane, Peters & MacGregor, 2004), our inability to correctly read statistics (Tversky & Kahneman, 1971; Kahneman & Tversky, 1972) and our unique manners in mental accounting (Thaler, 1985), there are a number of other decision making phenomenons that point to poor performance in human management. And those are just a handful of examples. People are miscalibrated by nature. Since the seminal works of Herbert Simon (1955), the limits of or rationality is an ongoing field of study.

Rationally limited managers live their life as professional illusionists. The two main effects of positiveness in the human psique are: overconfidence and optimism (Baker, Ruback & Wurgler, 2006). The main result of overconfidence? Optimism. The optimistic managers build strategies on a series of pipe dreams scenarios. In finance language, the future cash flows are overestimated and the amount is discounted at an underestimated rate. Furthermore, the optimistic manager brings some more systematic acts to the table: the optimistic manager invests more, pays less dividends, repurchase a greater number of shares and is inclined to take long-term debt (Ben-David, Graham, & Harvey, 2007).

Human underlying bounded rationality and optimism could be hard-coded in the quantitative fund algorithm. However, feelings surfaced during crisis periods could act as and exogenous event capable of producing observable performance differences in man versus machine made decisions.

Data

Brazilian hedge fund database in provided by Economatica, within a 10-year span (from Jan/2011 to Aug/2020). Two types of assets were excluded due to non-active management practices, mainly: funds of funds (a pooled strategy that invests in other funds) and index funds (a portfolio strategy that aims to mimic and benchmark index's assets). Overall, final monthly database is comprised of 103,424 fund-period observations.

Identification of purely quantitative hedge funds demanded an individual investigation of management practices. First, assets that described itself as quantitative hedge funds were listed. Following this procedure, an e-mail was sent to confirm if all decision-making processes were executed by algorithms. To be included as a quantitative hedge fund in this study, a reply confirming pure algorithmic trading is needed. Quantitative hedge funds represent 2.85% of our sample. Data of hedge funds division by regular and quantitative practices is shown in Table 1.

Average total risk-free return is higher in regular hedge funds. However, these results are much more volatile when compared to quantitative hedge funds. On the other hand, quant funds present better results in risk adjusted returns (Alphas), while still performing in a more stable rhythm.

Data from B3 (São Paulo's stock exchange) is used to develop proxies of market volatility and for crisis periods. Two different indexes are considered as benchmark for market returns, IBOV (companies with greater trading volumes) and IBRX 100 (companies with largest market capitalizations). Monthly SELIC is considered as Brazil`s risk-free rate.

Table 1

Descriptive statistics of hedge fund database. Total number of hedge funds, average performance measures and standard deviation are organized into Regular and Quantitative practices. Average asset under management is in Brazilian Reais (R$). Data is collected from Economatica database.

	Traditional	**Quantitative**
Hedge funds	784	23
Average risk-free return	1,33%	1,06%
Standard deviation of risk-free return	57,50%	2,88%
Average Alphas	0,24%	0,33%
Standard deviation of Alphas	3,40%	0,48%
Average assets under management	406.669.639,51	133.389.117,39

Methodology

A diff-in-diff strategy is developed within panel data OLS regressions to assess the performance of quantitative hedge funds in crisis periods.

The full sample is comprised by 128 months. To create a dummy variable for crisis periods, any sequence of negative performing three-day period below -5% as a period where behavioral biases may appear in regular decision-making is considered. The results are measured considering indexes as benchmarks. Following this premise, 48 crisis periods are identified by IBOV and 34 by IBRX 100, as shown in Table 2.

Table 2.

Identified crisis periods measured by market indexes (IBOV, IBRX) and pessimistic periods measured by Baker and Wurgler's sentiment index.

	IBOV crisis	IBRX crisis	BW's pessimistic
Months in sample	24	16	98
Frequency	20,69%	13,79%	84,48%

To try and further understand performance differences among bear periods, a market sentiment proxy, developed following Santana *et al* (2020) brazilian proceedings of Baker and Wurgler (2007) seminal work. This tool allowed to identify almost 85% of the sample period as pessimistic moments for Brazil's capital markets.

The dependent variables analyzed in this paper addresses hedge fund performance, considering risk-free monthly return (Return) and risk-adjusted monthly return (Alphas). The Independent variable is a *diff-in-diff* instrument (DD) are a pair of dummies that characterize Quant hedge funds (Quant) and crisis periods (Crisis). Market volatility and hedge fund size are used as control mechanisms. Equation 1 presents the basic random effects regression design.

$$R_{i,t} = \alpha + \beta_1 DD_{i,t} + \beta_2 Quant_{i,t} + \beta_3 Crisis_{i,t} + \beta_4 Controls_{i,t} + \varepsilon_{i,t} \tag{01}$$

Results Analysis

This section details empirical results on the performance comparison on quantitative and regular hedge fund management practices under crisis periods.

First regression analysis considers IBOV index for crisis identification. Results show that, measuring by total risk-free return, quantitative hedge funds perform significantly better in crisis periods than regular hedge funds, averaging a positive 27% at 1% significance level with control variables. Results are published on Table 3.

Table 3.

Results for OLS regression with random effects considering IBOV index as market benchmark. Tests are applied on monthly panel data from JAN/2011 to OCT/2020. Dependent variables are total Risk-free returns and Risk-adjusted returns. Independent variable is Quant x IBOV crisis, a diff-in-diff instrument created by a dummy variable for quantitative hedge funds (Quant.) and crisis periods (IBOV crisis). Control variables are Market volatility and Size (total equity). Data is collected from Economatica.

	Risk-free returns		Risk-adjusted returns	
Quant. x IBOV crisis	0.265**	0.271***	-0.081	-0.100
	(0.10)	(0.10)	(0.10)	(0.10)
Quant.	0.121	0.124	0.477**	0.512***
	(0.16)	(0.16)	(0.19)	(0.18)
IBOV crisis	0.019	-0.154***	0.073***	0.076***
	(0.02)	(0.02)	(0.02)	(0.02)
Market volatility		1.335***		0.000
		(0.08)		(0.05)
Size		-0.030*		0.114***
		(0.02)		(0.03)
constant	-4.731***	-4.473***	-6.245***	-8.359***
	(0.05)	(0.28)	(0.06)	(0.55)
R^2	0.001	0.024	0.003	0.001
N	24.117.000	23.261.000	18.350.000	17.562.000

* p<0.1, ** p<0.05, *** p<0.01

Considering risk adjusted returns (Alphas), quantitative hedge funds perform significantly better than regular hedge funds overall (not during crisis periods). However, the diff-in-diff instrument is not statistically significant when considering risk-adjusted returns. Meaning that, when measured by Alphas, the difference between regular and quantitative hedge funds performance is not affected by crisis periods.

A different metric for crisis periods is considered on the following test. The IBRX 100 index is used to develop proxies, identifying fewer crisis periods. Regression results are qualitatively similar to prior results. Quantitative hedge funds have better performance during crisis periods when measured by risk-free returns and overall better performance when measured by risk-adjusted returns. However, the economic impact on hedge fund results is stronger for both measures. Results are presented in Table 4.

Table 4.

Results for OLS regression with random effects considering IBRX100 index as market benchmark. Tests are applied on panel data from JAN/2011 to OCT/2020. Dependent variables are total Risk-free returns and Risk-adjusted returns. Independent variable is Quant x IBRX crisis, a diff-in-diff instrument created by a dummy variable for quantitative hedge funds (Quant.) and crisis periods

(IBRX crisis). Control variables are Market volatility and Size (total equity). Data is collected from economatica.

	Risk-free returns		Risk-adjusted returns	
Quant. x IBRX crisis	0.370***	0.399***	0.046	0.046
	(0.09)	(0.08)	(0.07)	(0.06)
Quant.	0.113	0.113	0.453**	0.483***
	(0.16)	(0.15)	(0.19)	(0.18)
IBRX crisis	0.058**	-0.127***	0.020	-0.004
	(0.02)	(0.03)	(0.02)	(0.02)
Market volatility		1.280***		0.083*
		(0.08)		(0.05)
Size		-0.029*		0.113***
		(0.02)		(0.03)
constant	-4.737***	-4.488***	-6.233***	-8.348***
	(0.05)	(0.28)	(0.06)	(0.55)
R^2	0.002	0.021	0.003	0.001
N	24.117.000	23.261.000	18.350.000	17.562.000

* p<0.1, ** p<0.05, *** p<0.01

Next, BW's investor sentiment is considered to smoothen the proxy for crisis periods. In this test, pessimistic periods are considered in constructing the diff-in-diff instrument. This presents an important change, since 84% of sample's months have been identified as pessimistic in Brazilian market. However, results do not differ from previous tests. Quantitative hedge fund has the upper hand in crisis periods when considering risk-free returns and overall superiority when considered risk adjusted returns. Results can be seen in Table 5.

Table 5.

Results for OLS regression with random effects considering BW's market sentiment as proxy for pessimistic periods. Tests are applied on panel data from JAN/2011 to OCT/2020. Dependent variables are total Risk-free returns and Risk-adjusted returns. Independent variable is Quanti x BW's <0, a diff-in-diff instrument created by the product of a dummy variable for quantitative hedge funds (Quant.) and a dummy variable for pessimistic periods (BW<0). Control variables are Market volatility and Size (total equity). Data is collected from economatica.

	Risk-free returns		Risk-adjusted returns	
Quant. x BW < 0	0.238***	0.245***	-0.051	0.013
	-0.09	-0.09	-0.08	-0.09
Quant.	0.013	0.004	0.491**	0.479**
	-0.17	-0.16	-0.2	-0.2
BW < 0	-0.287***	-0.291***	-0.136***	-0.115***

	-0.02	-0.02	-0.03	-0.03
Market volatility		1.118***		0.091*
		-0.07		-0.05
Size		-0.046***		0.106***
		-0.02		-0.03
constant	-4.545***	-3.984***	-6.135***	-8.140***
R^2	0,016	0,04	0,009	0
N	24.117.000	23.261.000	18.350.000	17.562.000

* p<0.1, ** p<0.05, *** p<0.01

Both tests present similar results, providing evidence that quantitative hedge funds perform better during crisis periods when measured by total risk-free return. Considering Alphas as performance measure, Quantitative hedge funds have superior performance overall. The difference between crisis periods and non-crisis periods with risk-adjusted performance is not statistically significant. The next test is designed to address this feature.

Data panel regressions considering full sample period are tested to understand the persistence of quantitative hedge funds performance, especially when measured by risk-adjusted returns. Results confirm the evidence of superior performance of quantitative hedge funds measured by Alphas: algorithm decision-making funds perform 49% better than traditional management throughout the sample period.

Table 6.

Results for OLS regression with random effects. Tests are applied on panel data from JAN/2011 to OCT/2020. Dependent variables are total Risk-free returns and Risk-adjusted returns. Independent variable is a dummy variable for quantitative hedge funds (Quant). Control variables are Market volatility and Size (total equity). Data is collected from economatica.

	Risk-free returns		Risk-adjusted returns	
Quant	0.169	0.170	0.460**	0.491***
	(0.16)	(0.15)	(0.19)	(0.18)
Market volatility		1.160***		0.080*
		(0.07)		(0.05)
Size		-0.029*		0.113***
		(0.02)		(0.03)
constant	-4.728***	-4.482***	-6.229***	-8.350***
	(0.05)	(0.28)	(0.06)	(0.55)
R^2	0.001	0.021	0.003	0.001
N	24.117.000	23.261.000	18.350.000	17.562.000

* p<0.1, ** p<0.05, *** p<0.01

Conclusion/Contribution

The objective of this paper is to assess the performance of quantitative hedge funds during crisis periods. To achieve this goal, a diff-in-diff strategy is designed using traditional hedge funds and proxies for crisis periods. The applied model uses random effects on panel data from Brazilian hedge fund industry from Jan/2010 to Aug/2020. The hypothesis states that algorithm asset management provides better results due to the absence of human sentiment-induced bias.

Empirical results show that quantitative hedge funds perform significantly better than regular hedge funds. Measured by risk-free returns and considering IBOV index as a proxy for market activity, quantitative hedge funds perform 27% better during crisis periods. When risk-adjusted returns are considered as the independent variable, quantitative hedge funds have 52% better results overall, with no significant difference between crisis and regular periods. Similar results appear by considering another proxy for market activity (IBRX 100) and when considering different measures for crisis periods.

Panel data regressions on the full sample period is proposed to test the intuition that risk-adjusted returns indicate a vast superiority of quantitative hedge funds, considering only the dummy variable that identify such practice. Results confirm this feature only when measured by Alphas. Overall results suggest a superior performance of quantitative hedge funds in the Brazilian market.

The paper`s main hypothesis states that machine driven choices should produce positive results compared to human management finds support in empirical tests. The qualitative approach to identify quantitative funds, crisis identification strategy, diff-in-diff application and BW's investors sentiment assessment provided quality tools to better understand the role of human induced sentiment in Brazilian hedge fund industry. Future research pathways could address cross-country databases, alternative strategies for crisis identification and simulations regarding the perspective of individual investors.

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