Report
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Particles and Purposes

Financial and capital markets can be described in various ways. One of the analogies that seems most appropriate to us is to treat them as an ecosystem. In fact, markets contain a large number of participating "species" competing and cooperating in a network of interactions. The dynamics of markets exhibit patterns of evolutionary requirements similar to communities of living organisms where financial results determine the energy efficiency and degree of adaptation of each individual in this environment.

From an aggregate perspective, transparent and liquid markets usually provide the price signals for an adequate allocation of savings, thereby making resources available for investment projects that push economies forward and promote social welfare. Behind this emerging macro-visible property lies a dynamic process of creative destruction where the competence of financial participants is measured by their ability to find assets backed by consistent returns over time. On this micro scale, competition is intense, with each participant seeking to develop and improve their own tools in order to gain some advantage, which essentially may be informational, institutional, analytical, or behavioral. The combination of these attributes establishes each individual's position in their niche and determines their success or failure in adapting.

Any highly competitive environment is ripe for innovation, and here it's no different. The multiplicity of asset classes and the huge number of financial products highlight the industry's high level of specialization. Sophisticated savers demand ever more customization and greater granularity in services. Managers try to discern some differentiating factor that will make them particularly worthy of investors' trust and thus stand out from the competition.

In recent decades, the dizzying increase in digital information, the development of various technologies such as electronic trading platforms leading to the replacement of traditional trading floors, computers with high processing capacity, more sophisticated software programs, the use of big data and analytics, machine learning (ML) and artificial intelligence (AI), have fostered a proliferation of certain "species" that employ systematic or quantitative methods as their main investment strategy and participation in market trading. More recently, another derivative of this digital technological progress is manifested in the unprecedented use of social media, resulting in a significant increase in the participation of individuals who use these vehicles as a platform for their activities on the capital market.

Still availing of the biological metaphor, in taxonomic terms, investors can be considered a broad genus, harboring multiple species. As traditional value investors, we share the same geography with the quants; sometimes we compete in the same niche (equities in Brazil), but we also seek survival and differentiation through consistent returns, even though we use very different tools and strategies. Increasingly abundant in a digital environment, data is the basis of the food chain for quantitative individuals. Nourished by this abundance of available inputs, systematic strategies using statistical treatment and automatic execution expand rapidly.

In the United States, algorithms are already responsible for around 70% of trading on the stock market, and for more than half of trading on futures markets (IMF, 2024)[1]. Even though we know that the level of penetration of this approach in other regions of the planet, including Brazil, is quite different (around 50% in Europe, 40% in Asia, and 30% in Latin America), we are already beginning to see in the dynamics of trading in our market initial suspicions of what seems to reflect patterns observed abroad.

We have a permanent interest here at Dynamo in observing, investigating, and discussing internally how any new trends or configurations in the environment can affect our status as a long-term investor and eventually have repercussions on our performance. This Report and the next one outline some reflections on this respected tribe of systematic strategies. As we don't intend to challenge our

1 *As usual, the full bibliographical references used in this text can be found on our website,* https://www.dynamo.com.br/pt/biblioteca.

circle of competence, we have narrowed the scope of our sample and focused on just three categories in this vast universe: high frequency trading (HFTs), factor investing, and passive strategies.

Once again, because the text has become long and dense, we've divided up the task: in this Report we'll deal with the HFT strategy, factor investing, and we'll take the opportunity to consider the phenomenon of "social trading," i.e., how digital media has left its footprints among investors. In the next one, we'll go through the journey of passive investments.

Algos/HFTs

Quantitative investors (quants) use mathematical models and statistical methods applied to a large volume of data in order to detect signs of opportunities and translate them into trading rules. The idea is to find regularities that can be transformed into valid inputs for determining future price behavior. Algos (algorithmic trading) employ computer programs with predefined instructions on a historical database in order to automate investment decisions and order executions. The menu of strategies is extensive. So just to mention a few: *HFT* (high frequency trading) uses advanced algorithms to identify price discrepancies, short-term statistical relationships (such as trend, coupling, reversal, etc.), and executes orders at high speed. The strategy of *trend following* seeks to exploit the momentum of price movements through technical metrics and more modern variants such as filters, as well as tracking sometimes non-linear combinations of these metrics. *Mean reversion* uses statistical techniques or machine learning (ML) models to take advantage of the understanding that prices tend to revert to their historical averages. *Arbitrage* strategies look at price discrepancies between different financial instruments or markets. *Statistical arbitrage* attempts to exploit the discrepancies between different financial instruments by executing trades based on statistical relationships; it employs various techniques, such as trading pairs, trading convergence, and event-driven arbitrage. *Market making* offers liquidity to the market by using algorithms to establish buy and sell prices according to the supply and demand conditions at any given time.

HFTs (or ultra HFTs) are a relevant subgroup of algos, as they also employ computer programs to implement investment decisions and trading strategies, but with the additional characteristic of seeking the fastest possible access to platforms and market information. Speed is a critical element in HFT, which specializes in exploiting small, transient profit opportunities with a "winner takes all" feature, i.e., where first-mover value is quite substantial. In the quest for superior speed, HFTs try to reduce as much as possible *latency*, which is the time lag for receiving, processing and responding to information. Some HFTs are capable of modifying messages in as little as 10 microseconds, which turns the blink of an eye into an operation thousands of times slower. Hence the heavy investment in processing capacity, software, and technological infrastructure, which includes state-of-the-art servers, data centers, and communication networks.

Speed is also optimized through access to the infrastructure of trading platforms. This is the case with *co-location* services, which enable participants to rent a position in the exchanges' data centers in order to store their servers, equipment, and applications. In addition to physical space, exchanges also usually offer infrastructure (security, electricity, air conditioning) and privileged access to their trading systems. We know that other investor profiles also use this service, thus it's not monopolized by HFTs. Even so, it's estimated that currently around 50% of the volume of shares traded on B3 is via co-location.

Since HFTs came to prominence in the late 2000s, numerous academic studies have debated their impact on market efficiency and stability. In positive terms, it is argued that HFTs shorten the bid-ask spread, reduce the time of non-arbitrated opportunities, increase liquidity, and improve the price discovery process, thus contributing to greater market efficiency. In addition, some point out that algorithms reduce traders' idiosyncrasies and emotional reflexes, thereby bringing more "rationality" to the trading desk.

If HFTs trade faster than other traders, in theory they should contribute to the price discovery process, precisely because they increase the speed at which new information is incorporated into prices. At this point, some critics are already raising counterarguments. For example, strictly speaking, HFTs don't produce or discover new information. They hitch a ride on the acquisition of information by slower traders. As HFTs have an advantage in terms of speed over others, these slower traders will tend to leave the market. This is something which is seen as adverse selection in the sense that they will no longer exploit longer-term opportunities (long-lived information), possibly reducing efficiency and liquidity (Biais & Foucault, 2014). In addition, there is a trade-off between speed and accuracy. Information is sometimes inaccurate or misleading. High-frequency investors reacting instantly to news can interpret noise as signals and inject more disturbance into the system, thereby drifting the market into a less efficient position. As their reaction-functions are not necessarily related to the fundamental value of the assets, we often see prices in our day-to-day showing sharp swings without any apparent basis.

In the US market, there is growing empirical evidence that HFTs pose more challenges than providing benefits. These include: (i) fragility of fragmentation. When orders are executed through several venues, the market becomes fragmented and dispersed rather than concentrated. Fragmentation prevents the market from functioning properly, making it difficult for investors to access not only the best prices, but in some cases the trading environments themselves[2]; (ii) increased volatility. The strategy's need to exploit price discrepancies at every minimum interval can generate a self-feeding effect when the large volume of orders amplifies market movements; (iii) asymmetry, concentration of power, and even possible market manipulation, in cases that escape effective regulatory surveillance. HFTs allow a limited number of participants to outperform other operators by exploiting greater speed (due to technological superiority), faster networks, and co-location. These advantages can facilitate inappropriate conduct such as the tactic of flooding the market with orders to gain speed, placing and canceling "fake" orders to cause illusion, creating a false sense of abundant demand or artificially producing price movements; (iv) concern about the integrity of the ecosystem, resulting from (ii), since the way HFTs respond to market conditions tends to cause more abrupt price swings, which can be accompanied by cascading effects and contagion, even inducing a more systemic collapse; (v) front running, especially in situations where there is payment for order flow .

Despite the large number of different players, systematic investors generally seem to follow more similar strategies, have more homogeneous portfolios, analyze past data in a similar way, follow the same signals, and reach closer conclusions. As such, being more influenced by their peers and entering and exiting the market in a more coordinated manner, they are likely to make more similar trading decisions (Beggs et al., 2019).

Empirical studies show that among this category of investors, forced sales induced by flows (*fire sales*) tend to generate price drops around five times sharper than among non-quantitative funds; then takes three times longer for stocks to return to their fundamental value. In order to explain such significant results, the authors (Beggs et al., 2019) tested several hypotheses and found statistical significance for two aspects: (i) a greater overlap of portfolios, which increases the possibility of quantitative funds liquidating similar positions simultaneously; (ii) a heavier reliance on past price momentum in their sell decisions. In other words, quantitative strategies tend to continue selling what has fallen recently, which causes a negative spiral effect in returns. The effects are self-reinforcing, since (ii) induces (i), which in turn tends to feed (ii). The result is that stocks liquidated by quantitative investors are more likely to enter a negative feedback loop with sharper and longer-lasting falls.

At this point, it seems hard to resist the evidence that the massive use of high-frequency algorithms contributes to pushing prices away from fundamentals. The event known as the flash crash of the US stock markets in 2010 set off a warning signal about the potential destabilizing effects of HFTs. On May 6 of that year, the Dow Jones, S&P 500 and Nasdaq indices collapsed and recovered in a matter of minutes. The Dow Jones plummeted 9%, the second biggest intraday drop in its century-long history. After countless investigations and academic articles, it is now known that HFTs were not the primary cause of the phenomenon but contributed decisively to its spread. In times of market stress, when prices move in a single direction reflecting the imbalance of order flow, the activity of HFTs acts pro-cyclically, exacerbating this directional movement and contributing to increased volatility (Kirilenko et al., 2014). In other words, the massive presence of algorithms and systematic rules can cause "self-reflexivity" effects in the markets, when price movements are motivated by the prices themselves.

Value

The availability of high-quality, high-frequency data is transforming the discipline of finance. This data offers a more detailed description, not only of asset prices but also of the actions and interactions of market participants. When this remarkable volume of information becomes more accessible and comprehensive, a new field of study blossoms around a concept called *market microstructure*, a discipline that has garnered growing interest from the academic community, the effect of which is instantiated in a significant increase in the number of specialized publications.

2 *A recent Bloomberg report (Doherty, 2025) finds that, for the first time, most of the stock trading in the United States took place outside the traditional stock exchanges (NYSE and Nasdaq), raising concerns about the consequences for the efficiency of market prices, as well as the costs for investors and issuers.*

In the view of those sympathetic to this approach, this wealth of information reveals an unprecedented insight into the inner workings of the financial ecosystem, sparking enthusiastic inspiration. *"Just as the atomic hypothesis allowed Maxwell and Boltzmann, 150 years ago, to understand how the macroscopic world is described by thermodynamics, trades and quotes are the elementary units from which price dynamics emerges."* (Bouchaud, 2022).

On another spectrum of this vast ecosystem, contemplating a different perspective from this quant reality that sees buy and sell orders as physical particles, are the fundamentalist investors. *Value investing* is an active way of investing that basically combines two ingredients: a conviction and a premise. The first consists of the understanding that it is possible to understand the intrinsic value levers of companies and identify asset prices distortions. The second assumes that the market will perceive these asymmetries over time and converge prices in the direction of the reliable ballast of value.

Historically, investors in this niche have concentrated their efforts on the first variable in the equation, seeking to develop specific skills that will give them some advantage in this lonely and almost presumptuous journey of recognizing something that others are not yet seeing.

Regarding the second part, as is well known, value investors don't agree with the efficient markets hypothesis (EMH) either. According to this influential premise, market prices instantly capture all available information and reflect the intrinsic value of assets at every moment in time. Therefore, it would not be possible to make valid inferences about the future behavior of prices, as they fluctuate randomly driven only by the arrival of new information.

Our understanding is that most of the time, markets play their role of aggregating information, updating dispersed expectations and opinions, reflecting the principle of the "wisdom of crowds" (Surowiecki, 2004), which ends up resulting in small variations in prices. However, moments of greater uncertainty generate insecurity and provoke imitative and more emotionally charged behavior. The basis of diversity and independence in the formation of opinions is broken and the rational assessment of risk-return is compromised. When the power of local intelligence is atrophied, decisions accumulate in the same direction and are reinforced by positive feedback effects. As a result, the most extreme or "abnormal" variations in prices arise. These are moments of crisis or market "adjustments," occasions for patient investors to enter the field.

And so the cyclothymic market has always been seen as an ally for this tribe of participants, offering entry and exit opportunities at attractive prices in times of excess. Once the emotional extremes have passed, in times of greater psychological sobriety, rationality once again prevails and seeks to locate prices where disciplined value investors imagine they will stay or take off. Sometimes, investors in this category believe it is necessary to promote initiatives (activist engagement) as a way of catalyzing the desired convergence, an implicit premise of the second ingredient. These considerations are important because they underpin our convictions and determine our investment philosophy here at Dynamo, which ends up guiding all our analysis and management work.

Underneath this value-centered clave resides the understanding that prices express the intentional actions of participants, capturing a broad spectrum of different and even divergent views. Those who believe that prices should rise (fall) buy (sell) in anticipation of this movement. Buyers want to acquire assets at the lowest possible price and sellers, in turn, want to sell them at the highest possible value. Each entity, in each interaction, wishes to maximize its surplus.

Trade is the common thread that reveals private information about the fundamental value. The countless trades interactions bring buyers and sellers closer together until the point of intersection between them, where the transaction finally takes place, creating the process known as "price discovery." It's no wonder that the subject of trade is the object of extensive study. If price is the meeting point between supply and demand, trades are a powerful tool for leading to this convergence, the magic point where *price discovery* becomes just *price*.

In contrast, the quant approach rests on a disbelieving understanding of the participants' purposes or the informational content of negotiations. For them, the very trades in themselves have an impact on prices. The interest lies in the act of trading itself, in the perception that each sale and purchase leaves its "physical" footprint on the market and, when aggregated, becomes a statistical matter. Under this agnostic view of the informational content of trades, the semantics change subtly: we no longer speak of price discovery, but of price formation.

On the short time scale of a few seconds to a few days, the notion of fundamental value becomes secondary to understanding price dynamics, since the frequency of new information that affects the fundamental value of financial assets in this very short period of time is much lower than the frequency of price changes. It's as if the price changes themselves were responsible for the main sources of news. In fact, quantitative interactive models, which capture feedback elements, suggest that at least 80% of the variance in price is induced by self-referential effects, leading to the conclusion that most of the short-term activity in the market would not be related to information about fundamentals or economic magnitudes (Bouchaud et al., 2018)

This separation between price and fundamentals opened up space for the development of a theory of price movements essentially based on market dynamics governed by endogenous elements, when prices move simply because trades are taking place, and not for any other intentional or fundamental reason. This is a proposition that presupposes a real paradigm shift: prices are no longer guided by fundamentals, but by the flow of buy and sell orders, whether informed or random. All of this is very convenient from a quantitative point of view, since considering long-term fundamental effects makes it very difficult to deal with in a purely mathematical-statistical model.

Of course, we value investors find it extremely difficult to accept this approach at face value. Investing consists in its essence of carrying out fundamental analysis work. Value comes from this activity; trading synthesizes this work by expressing it in the form of price. Stripping trading of teleological arguments seems to us to be a mistaken reductionism. Shares are not physical particles. Shares are certificates of measurement of a reality that changes all the time, just like a living organism. Those who trade shares do so based on an interpretation, a context, and a world view. What drives the order book are arguments and purposes. An order to buy (or sell) a particular share made by the company itself (buyback program), by the reference shareholder, by the directors, by a strategic investor, conveys a completely different informational content to that of an individual, or of an investor forced to operate according to institutional/regulatory imperatives.

Factors

Another important group of systematic investors are those who employ *factor investing* strategies. Factors are properties common to a set of assets that help explain differences in their returns. Investors who follow this approach try to identify these systematic attributes, separating noise from signals, in order to build portfolios that present better risk-adjusted returns from each specific mandate. Value, momentum, size, quality, and volatility are the styles of factors most commonly used in the stock market. There are also macro factors, including economic growth, inflation, interest rates, and foreign exchange, which influence the performance of assets and serve as a parameter for measuring the degree of protection of portfolios. There are several possible metrics for each factor, for example, *value* can be measured by price/earnings per share (P/E), price to book (P/B), price/free cash flow (P/FCF), EV/EBITDA, etc. In terms of *quality*, metrics such as profitability, low leverage, return, credit rating, and margin stability, among others, are usually used.

There is a large, documented number of different factors, reaching a few hundred, as well as different taxonomies. *Growth* is sometimes considered a separate factor; sometimes it appears as one of the metrics of the *quality* factor. *Dividend* is a factor for some, but not for all. In this vast "zoo" (Cochrane, 2011), it is necessary to identify the most promising ones. Among the main demarcation parameters, it has already been said that factors need to be persistent (able to generate excess returns over time); pervasive (able to be verified across different sectors and geographies); robust (valid for various verification tests and definitions), investable (able to be implemented in practice and not just on paper), and intuitive (endowed with economic logic and well explained in behavioral terms) (Berkin & Swedroe, 2017.) Statistically, when they are well combined in a so-called multifactorial strategy, the results tend to be better.

Factor investors present themselves as a middle ground between the two extremes (pure quantitative and traditional value investors), since they develop systematic strategies derived from metrics based on fundamentals. The narrative is that "*quantamental*" investing – part quantitative, part fundamentalist – has emerged as an "evolution," bringing together the best of the two previously well-separated approaches: *"The advantage of two engines is that when one doesn't work, the other one might"* (Slimmon & Delany, 2018). Ex-post, on paper, a seemingly irrefutable logic.

The process of systematic factor investing involves a number of steps. First, the analysis of data, such as price, asset volume (microstructure), fundamentalist metrics and macro indicators. In certain situations, this stage requires some discretion, when structured data is corrected and "edited" in order to avoid, for example, accounting distortions. More modern versions have sought to work with unstructured data generated on e-commerce platforms or by reading and interpreting text and voice via natural language processing models. The next phase is the refinement of the data library, as well as the construction/testing of new metrics/factors. This is when the zoo factor is tested and formulated. The third stage consists of selecting and combining factors in order to build a strategy, when "families" are formulated, and ML techniques are used. The last stage is the final construction of the portfolio and the development of rebalancing systems to make execution more efficient after costs.

It is important to note that the "production line" of factor investors starts with numerical data as the basic raw material, which feeds proprietary statistical models in order to generate systematic rules and thus guide portfolio construction. Structured data and statistical models are therefore at the heart of the strategy. Fundamental investors, on the other hand, perform a bottom-up analysis, based on more qualitative, uncoded information and a more holistic approach, using quantitative techniques only as an auxiliary tool in their analysis work. With the increasing digitalization of economies, production processes, and consumer experiences, traditional value investors are testing the possibility of developing quantitative treatments, that is, algorithms that track information available on the internet and software programs that organize unstructured databases in order to access a set of information that is difficult to perceive with the naked eye. We here at Dynamo are also incorporating this geometry into our daily work. This is absolutely not a strategic move, but just another expression of the ongoing quest to improve our analytical tools.

Although we have no specific experience in building a factor portfolio, we understand that the task involves many challenges[3]. You have to work with a large amount of data and define the demarcation criteria. For example, on the basis of which P/E reference should the group of expensive (short) and cheap (long) stocks be classified? How can the increasingly present reality of intangible assets be taken into account in the P/BV metric? There are known pitfalls that also need to be addressed. It is known that *momentum* strategies tend to show higher returns over time. However, in times of sharp market fluctuations, such as during the 2008 financial crisis and the Covid pandemic, this factor can wipe out a large part of the results because it tends to perform worse both in the fall and in the recovery, since the strategy is unable to "risk-off" the positions in time. It is also known that some factors perform well in certain periods and not so well in others. The *trend following* strategy, widely used in futures markets, is also based on price persistence patterns, but unlike momentum (*cross-sectional*), it focuses on an asset class over time (*time series*). The technique was able to deliver consistent results over an extended period, from the late 1980s until the 2008 financial crisis. From then on, with the flood of government money to stimulate the economy, the Fed launched a long season of easing interventions (changing the dynamics of trends, which became much shorter and with gaps, especially in the bond market), making it practically prohibitive to carry short positions in this asset. As a result, some funds specializing in *trend following* models were forced to close their doors. In fact, more experienced factor investors have been pointing to this "exuberance" of macro policies, the orchestrated work of governments and central banks promoting successive unprecedented injections of liquidity into economies, as the main generator of distortions, making it difficult for statistical models to adhere to expected historical patterns.

It's no surprise that some factors perform well during certain periods and not so well in others. The economy is a cyclical activity, and financial markets are subject to fluctuations and changes in trend. Any approach that tries to infer the future from past performance encounters particular difficulty at times of transition. By definition, when the environment changes, what seemed to be a behavior well-adjusted to the previous reality starts to face adaptive challenges. It's no coincidence that companies going through M&As, a period of transition par excellence whose outcome is very difficult to infer, are often muted from the factor filters, being treated as pure noise.

More recently, the use of ML and AI tools has been increasing among factor investors, used at various stages of the process: in execution, in the treatment of data – structured and unstructured – in risk management, in the selection of metrics and in portfolio construction itself. We have also seen the growing use of natural language processing models used as an analysis tool to capture "sentiment" in company earnings releases and conferences, as well as in social media groups. As an example, the tools count and compare the number of times words such as "growth," "reduction," "favorable," and "difficult" appear in earnings release documents and try to anticipate market reactions. Factor managers have also revealed that ML and AI tools sometimes suggest strategies that are apparently difficult to understand in their "traditional" mental models, hinting at how promising they might turn out to be.

As price dynamics cause daily shifts in individual performance and portfolio composition, investing in factors

3 *Here we would like to acknowledge our debt to several quantitative fund managers who have been generous interlocutors over the years. Despite our different views, they have always been patient with our curiosities about topics that are not within our strict circle of competence. In particular, we would like to thank Marcello Paixão of Bayes Capital Management, one of the pioneers of factor strategies in Brazil.*

requires periodic rebalancing in order to align asset weights with the desired exposure, maintain diversification, and adjust the portfolio's risk profile. Frequent recalibrations can incur significant transaction costs and taxes, as well as requiring a good reading of both market timing and the life cycle of each factor.

Because of all these elements, even though they start with data, use quantitative methods and obey systematic portfolio construction rules, the manager of a factor strategy behaves like an active manager and, to a certain extent, a discretionary one. Active because (a) they have to choose between hundreds of different styles (there are more factors than there are publicly traded companies on B3); (b) they are looking for differentiated returns and are not content with the market average, and (c) they are often participating in the market, buying and selling assets in the portfolio. Discretionary in the sense that the manager intentionally and qualitatively interferes in the process, adjusting the selection of assets, the design of the models and, performing out periodic reviews.

Even with all these challenges, the fact is that some investors in this space seem to have those rare skills of taming data with appropriate statistical treatments and exercising discretion with skill, obtaining consistent results over a long period of time. The recognition of these abilities has led to a colossal growth in these companies, giving them advantages of scale and a wide dominance of trading platforms. On Euronext, for example, 90% of the volume traded on equities is concentrated in just ten members (IMF, 2024). Faced with the need for high levels of specialization, the challenge of finding valid insights among a huge amount of data and developing algorithms and strategies capable of making the most of this volume of resources, the largest fund managers are home to hundreds of PhDs with diverse backgrounds, including physics, mathematics, statistics, and computer science. Even so, they face the trap of their own success, as George Soros put it so well almost thirty years ago: "*The more successful I was, the more I was punished by having more money to run*" (Bernstein, 1999).

Factor investors often present the approach as a "*quantitative way of expressing a qualitative theme*" (Berkin & Swedroe, 2017). Convinced of the power of their tools, they believe they can identify the "secret sauce" of any successful investor, including Warren Buffett. All they have to do is deconstruct and slice up the long history of performance data.

In an interview with Bloomberg, Cliff Asness (2023), the CIO of AQR, one of the most renowned systematic investment companies, explained the difference between the concept of value for quants/academics and for investors who follow the Graham-Dodd tradition, such as Warren Buffett. Value for the former is basically a metric that captures the relationship between price and fundamentals (price-earnings, price-cash flow), with the understanding that over time what is cheaper tends to perform better than what is more expensive. For those sympathetic to the second group, the elements described in this way relate more to prices, since value implies a more holistic approach that incorporates attributes such as growth opportunities, economic moats, considerations about how safe the stocks are, or about the good things that happen to companies.

At this point, Asness continues the interview:

> *If it ever gets this far, the quants should explain. We believe in all those same things, just semantically we call those separate factors, and we add it up. But that little miscommunication has caused a lot of differences. If you look at Warren Buffett's track record, as amazing as it is – no one would call Warren Buffett a quant. Yet he is very correlated with what quants would call the value factor, the low risk factor, and the profitability factor. He buys companies that make a lot of money, aren't very risky, and then he looks for a decent price.*

In Berkshire's case, the complexity of a holistic approach, the understanding of countless qualitative, subjective, and psychological elements, the patience and discipline to make incisive and timely moves, the specific experience accumulated over decades of analyzing

Dynamo Cougar x Ibovespa
Performance in R$ up to January 2025

Period	Dynamo Cougar	Ibovespa*
120 months	207,3%	168,9%
60 months	-2,8%	10,9%
36 months	-3,1%	12,5%
24 months	9,3%	11,2%
12 months	-3,2%	-1,3%
Year (2025)	5,5%	4,9%
Month (January)	5,5%	4,9%

(*) Ibovespa closing. Indices are presented as economic reference only, and not as a benchmark.

different businesses, of being close to the management of companies, of interaction with all stakeholders and in-depth knowledge of the corporate environment, thousands of hours of study and dedication to forming sophisticated mental models – all these elements and many others that make up the art of investing wisely, according to this line of argument, could be captured, synthesized, and expressed by correlations with three single magic factors: value, low risk, and profitability. Another well-known AQR partner, Antti Ilmanen, also applied his regressions to "demystify superstars" investors (Ilmanen, 2022) (in this case Buffett himself again) and concluded that Berkshire's long-term performance would be best explained by its "exposure to the market" and mainly due for the *quality* and *low-beta* factors, with the *value* factor making a smaller contribution to the composition of the results. In other words, according to these two analyses, the same quantity seems to have different decomposition rules.

For us, the difference between these two universes – systematic factor and fundamental value – seems much more than mere "semantics." Reverse-engineering ex-post results by associating them with a prefabricated shelf of "attributes" does not, in our view, help us become better investors. The numerical science of explaining "alpha" from past data doesn't seem to offer us sufficiently robust clues to produce alpha in the future. It's almost as if discovering that it's necessary to use varnishes between layers of thick paint, load up on the monochrome of golden tones, and insist on the juxtaposition of the chiaroscuro technique is enough to reproduce a Rembrandt etching. Our observation here is unpretentious and without any *value* judgment. Long live the diversity of the ecosystem!

Despite the affinity discourse, which reduces the differences in approach from traditional value investors to semantic issues, we believe that the growing popularity of factor investors may also contribute to a shift away from fundamentals, requiring more patience for convergence between price and intrinsic value. The proliferation of so-called extrapolative, momentum, and trend following strategies, which buy recent winners and sell losers, is a typical example. In periods of stretched valuations, the inertial (centrifugal) force of these strategies contributes to continuing to push prices in the same direction as in the past, eventually moving them further away from the gravitational (centripetal) anchor of the fundamentals, or, in the language of factors, even overcoming the mean-reverting forces of the value *tilts* (weights).

Social Media

The desire to participate in games of chance is deeply rooted in the human psyche. The association of the financial market with gambling behavior has also been widely documented. Investors trade stocks as a direct substitute for traditional forms of gambling, such as lotteries, casinos, and sports betting. Empirical studies provide a variety of evidence: the volume of stocks traded on the stock market decreases on days when large lotteries are drawn; or, too, casino regulars exhibit more aggressive financial market behavior. Others show alarming results: 14.4% of a sample of investors in Thailand and 21.5% in Korea show behaviors compatible with clinical descriptions of compulsive gamblers (Cox et al., 2020, 2020). In Dynamo Report 73, in an attempt to explain the reasons for the prevalence of a short-sighted mentality in the markets, we recalled the importance of the physiological component. There we said:

> *"When subjected to choices involving immediate payoffs, functional resonance imaging tests show an activation of structures in the limbic system, usually associated with emotional rewards. These structures are also connected to regions of the brain that release dopamine, a substance that makes us feel good, confident, and stimulated. In other words, a short-term financial investment decision where the expected return is immediate should be processed in a dominant way by our more impatient, impulsive, automatic, intuitive system" (Dynamo Report 73, 2012).*

In addition to the physiological root, other elements of a psychological and behavioral nature find ample stimulus in the financial market to manifest themselves: (a) the taste for checking and tallying results at every moment, especially when there is a monetary reward involved; (b) the overconfidence that drives individuals to want to gamble/trade more; (c) hyperbolic discounting, reflected in the fact that individuals attach great importance to near events, since they are less sensitive to distant choices, that is, we tend to prefer short trades; (d) the simple desire to experience a good feeling, taking a risk in order to feel excitement, or investment as entertainment; (e) the aspiration to make quick and easy money, among others.

More recently, another phenomenon has added even more fuel to these dispositions: digital technology, which provides almost permanent access to trading environments for financial products, as well as awakening and recruiting the important social component. The New York Stock Exchange (NYSE) has announced that it intends to expand the trading session to 22 hours on weekdays, meeting the manifest desire of investors, apparently already accustomed to the possibility of trading cryptocurrencies on their smartphones 24 hours a day, including weekends. There has also been an exponential increase in the number of social media popular financial "advisors", attracting attention of large network of communities capable of quickly spreading dubious trading recommendations.

Investment discipline obeys a risk-return logic, whose payoffs depend on the investment horizon. When retail investors disregard this basic template, they turn investments into bets, creating an extremely fertile trading environment for an even greater increase in statistical strategies. S&P 500 derivatives expiring on the same day, the so-called 0DTE (zero days until expiration), already account for half of the entire volume of derivatives on this index. When we add up the derivatives with up to 1 day to expire, we reach almost 2/3 of the total volume.

Here in Brazil, the number of individual investors trading on B3 has grown by around 40% a year in the last six years, reaching the mark of 5.2 million individual taxpayers in the latest available statistics, accounting for 14% of the total volume of the equity market, 31% of Brazilian depositary receipts (BDRs), 75% of real estate funds, 94% of funds linked to agribusiness (FIAGROs), and 30% of ETFs (B3, 2024). This "success" of retail investor participation comes with several concerns. In a document analyzing B3's proposal to expand the experimental RLP (retail liquidity provider) program, extending it to transactions of dollar and index futures mini-contracts, CVM found that the "significant increase in the investor base" was associated with "extremely worrying" results, noting that, in the period analyzed, 78% of investors lost money trading index mini-contracts and 81% lost on dollar contract trades. Among the various factors that could explain this negative result, the CVM pointed to the use of leverage and the presence of behavioral biases, explained as "cognitive shortcuts that cause distortions in decision-making and induce investors to ignore relevant factors that may impact their investments" (CVM, 2021).

The emergence of meme stocks illustrates the dynamics of this environment, and the shares of GameStop, a bricks-and-mortar video game retail chain, captures its most emblematic expression. The recommendation of investors engaged in social media quickly percolated through investor/follower communities and discussion forums on the internet. In January 2021, GameStop's stock appreciated no less than thirtyfold (from 17.25 USD to 500 USD), triggering a devastating short squeeze in some institutional investors who had a pessimistic view of the company's future performance in the face of the competitive threat from digital distribution in this segment.

Without going into the merits of the analysis of the fundaments, the fact is that investors on platforms such as WallStreetBets showed aggressive hostility towards those holding the short position, expressing the potential for market participants to organize a diffuse, open and anonymous collective action, even though it might be capable of producing very targeted results.

This has ushered in a new dimension of the capital market in times of social media. Hence, the "emerging property" where the perceived value of an asset lies in the message its price conveys, rather than in its intrinsic value. Something previously unimaginable, purposely distorting asset prices in order to create a disturbance of such magnitude as to force uneconomical behavior. A rational decision to take an apparently uneconomic stance ended up producing unreasonable investment decisions and forced managers who were making rational long-term decisions to literally throw in the towel, thereby demonstrating that risk management can be much more complex than buzzwords.

The idea of this Report was to share with our readers some reflections on the way in which certain profiles and behaviors of individuals who inhabit the market ecosystem are posing challenges for value investors like us. We have chosen two categories of systematic investors, high-frequency traders (HFTs) and factor investors, to illustrate the fact that, in pursuing their investment strategies, they can cause prices to move further away from the fundamentals, thus testing convictions and the rigor of our analysis work, as well as demanding more discipline and patience from our investors. We'd also like to take this opportunity to add a few brief comments on the more recent reality whereby investors are organizing themselves around social platforms – possibly resulting in behavior that has no connection to company operating performance.

We end by noting another oddity: the fact that a third of all S&P 500 stock trades have been executed in the last ten minutes of the trading session. And this pattern is also seen in Europe, where empirical studies suggest that the trend may be distorting price formation and

DYNAMO COUGAR x IBOVESPA (Performance in US$)*

Period	DYNAMO COUGAR Year	DYNAMO COUGAR Since Sep 1. 1993	IBOVESPA** Year	IBOVESPA** Since Sep 1. 1993
1993	38.8%	38.8%	7.7%	7.7%
1994	245.6%	379.5%	62.6%	75.1%
1995	-3.6%	362.2%	-14.0%	50.5%
1996	53.6%	609.8%	53.2%	130.6%
1997	-6.2%	565.5%	34.7%	210.6%
1998	-19.1%	438.1%	-38.5%	91.0%
1999	104.6%	1,001.2%	70.2%	224.9%
2000	3.0%	1,034.5%	-18.3%	165.4%
2001	-6.4%	962.4%	-25.0%	99.0%
2002	-7.9%	878.9%	-45.5%	8.5%
2003	93.9%	1,798.5%	141.3%	161.8%
2004	64.4%	3,020.2%	28.2%	235.7%
2005	41.2%	4,305.5%	44.8%	386.1%
2006	49.8%	6,498.3%	45.5%	607.5%
2007	59.7%	10,436.6%	73.4%	1,126.8%
2008	-47.1%	5,470.1%	-55.4%	446.5%
2009	143.7%	13,472.6%	145.2%	1,239.9%
2010	28.1%	17,282.0%	5.6%	1,331.8%
2011	-4.4%	16,514.5%	-27.3%	929.1%
2012	14.0%	18,844.6%	-1.4%	914.5%
2013	-7.3%	17,456.8%	-26.3%	647.9%
2014	-6.0%	16,401.5%	-14.4%	540.4%
2015	-23.3%	12,560.8%	-41.0%	277.6%
2016	42.4%	17,926.4%	66.5%	528.6%
2017	25.8%	22,574.0%	25.0%	685.6%
2018	-8.9%	20,567.8%	-1.8%	671.5%
2019	53.2%	31,570.4%	26.5%	875.9%
2020	-2.2%	30,886.1%	-20.2%	679.0%
2021	-23.0%	23,762.3%	-18.0%	538.9%
2022	-7.8%	21,899.9%	12.0%	615.4%
2023	32.1%	28,965.0%	31.8%	842.8%
2024	-30.8%	20,002.8%	-29.9%	560.7%
2025***	12.0%	22,423.8%	11.4%	635.9%

(*) Considering that this is a Fund that has existed since 1993. the figures were converted into dollars (US$) as a way to eliminate the volatility of the Brazilian currency throughout the period and. in this way. minimize the risk of possible misinterpretations by the reader in the case of an investment decision/ divestment. Dynamo Cougar is a fund that invests in NAV of an equity investment fund and is currently closed for new investments. (**) Ibovespa closing price. The index is presented as a mere economic reference and does not constitute a target or benchmark for the Fund. (***) Return up to January 2025.

producing adverse effects on liquidity, in terms of wider relative spreads and less depth in the order book (Bender et al., 2024). A relevant part of the explanation behind the phenomenon seems to be passive funds, which generally buy and sell shares at the end of trading sessions in order to minimize tracking error, since closing prices are used to benchmark the indices they intend to replicate.

But this story of passive investment deserves another Report...

Rio de Janeiro, 4th February 2025.

Additional information:

- **Inception**: 09/01/1993
- **Objective:** Deliver NAV appreciation above inflation in a medium/long term horizon by investing at least 95% (ninety-five percent) of the fund´s net worth in the NAV of Dynamo Cougar Master Equity Investment Fund ("Master Fund")
- **Target investor**: Qualified investors
- **Status:** Closed for new investments
- **Redemption grace period:** 12 months grace period or liquidity fee of 3% for redemption within this time period*
- **Redemption NAV:** D+12 (calendar days)*
- **Redemption payment:** D+2 (working days) after NAV conversion*
- **Applicable taxation:** Equity
- **Anbima´s classification:** "Equity – Free Portfolio"
- **Management fee:** 1.90% per year for the Fund + 0.10% for the Master Fund
- **Performance fee:** on the top of IPCA + IMAB*
- **Average monthly net worth last 12 months:** R$ 5.838,2 Million.

(*) Detailed description provided in the bylaws

To find more information about Dynamo and our funds. or if you wish to compare the performance of Dynamo Cougar to other indices in different time periods. please visit our website:

www.dynamo.com.br

DYNAMO

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