Valuation Decoded

A Framework for Identifying and Exploiting Market Inefficiencies

Savana Active ETFs · Internal Research

October 2025

Abstract

Savana is pioneering the application of Complex Adaptive Systems and Collective Intelligence science in financial markets.

Through this framework, we provide a new lens on market efficiency - one that acknowledges the market's brilliance in establishing fair value, while also identifying the rare but persistent conditions under which efficiency breaks down and mispricings emerge.

Savana's methodology is designed to recreate the Collective Intelligence of markets, but in a synthetic, objective, and data-driven form. This approach remains firmly anchored to intrinsic value even where market inefficiencies emerge, enabling us to systematically identify and exploit instances of mispricing.

This White Paper provides evidence that Savana's disciplined, model-driven replication of Collective Intelligence offers a credible pathway to a repeatable investment edge. If sustained, this methodology not only delivers a robust explanation of how inefficiencies can be harnessed, but also provides a powerful new framework for understanding and capturing the sources of market alpha.

Contents

Introduction

The debate over market efficiency remains central to financial economics. The Efficient Market Hypothesis (EMH) contends that asset prices fully incorporate available information[1], while behavioural and empirical evidence demonstrate persistent anomalies inconsistent with this view.[2] Reconciling these perspectives requires a framework that accommodates both efficiency and episodic breakdowns.

This paper advances such a framework by treating financial markets as a Complex Adaptive System (CAS). Within this construct, prices generally reflect intrinsic value through the mechanism of Collective Intelligence, whereby diverse and independent participants aggregate dispersed information. However, when diversity diminishes or independence is compromised, efficiency weakens and mispricings emerge.

Savana's methodology operationalises this framework through a synthetic data-driven form of Collective Intelligence. The analysis that follows demonstrates three key findings: (i) Savana's valuations broadly align with prevailing prices, affirming baseline efficiency; (ii) divergences are concentrated in smaller, less-covered companies, consistent with prevailing market theory; and (iii) these divergences possess predictive validity, as reflected in subsequent return behaviour and portfolio outcomes.

Ultimately, we show that while markets are efficient most of the time, their mistakes are both identifiable and exploitable, and it is precisely in those moments of breakdown that an enduring investment edge is found.

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[1] Fama, E. F. (1970). Efficient Capital Markets: *A Review of Theory and Empirical Work*. Journal of Finance, 25(2), 383–417.

[2] Gabriela, A. (2015). *The Efficient Market Hypothesis: Review of Specialized Literature and Empirical Research*. Procedia Economics and Finance, 32, 442-449.

Framing Markets as a Complex Adaptive System

Since the 1970s, economists have debated the Efficient Market Hypothesis (EMH) - the idea that asset prices fully reflect all available information, leaving no room for consistent outperformance. The “strong” form of EMH paints markets as a perfectly efficient, random walk, where price changes are entirely unpredictable. In contrast, behavioural finance and empirical anomalies suggest that markets can be inefficient, with exploitable patterns that persist for a time. [3]

Savana’s view lies somewhere between these poles. Markets are mostly efficient most of the time, not because every participant is rational, but because the collective interactions of millions of agents quickly compete away obvious mispricing. Any recurring pattern is often arbitraged out as soon as it becomes widely known, meaning that yesterday’s edge rarely survives tomorrow’s market.

This behaviour is characteristic of a Complex Adaptive System (CAS) - a dynamic network of interacting components that exhibits emergent behaviour, meaning the system's overall behaviour cannot be predicted from the behaviour of its individual parts. [4]

Framing markets this way changes the investment problem. Instead of seeking a single, timeless model of price behaviour, the challenge becomes building a framework that can adapt to changing regimes, learn from shifting relationships, and exploit the short-lived inefficiencies that appear before the system self-corrects.

It is within this adaptive, constantly evolving environment that Savana’s Collective Intelligence approach is designed to operate, recognising that predictive power lies not in extrapolating from the past, but in understanding the dynamics of the present.

[3] Brown, S. J. (2020). *The Efficient Market Hypothesis, the Financial Analysts Journal, and the Professional Status of Investment Management*. Financial Analysts Journal, 76(2), 5–14.

[4] Carmichael, T., & Hadžikadić, M. (2019). *The Fundamentals of Complex Adaptive Systems. In Understanding Complex Systems* (UCS). Springer.

Introducing Collective Intelligence

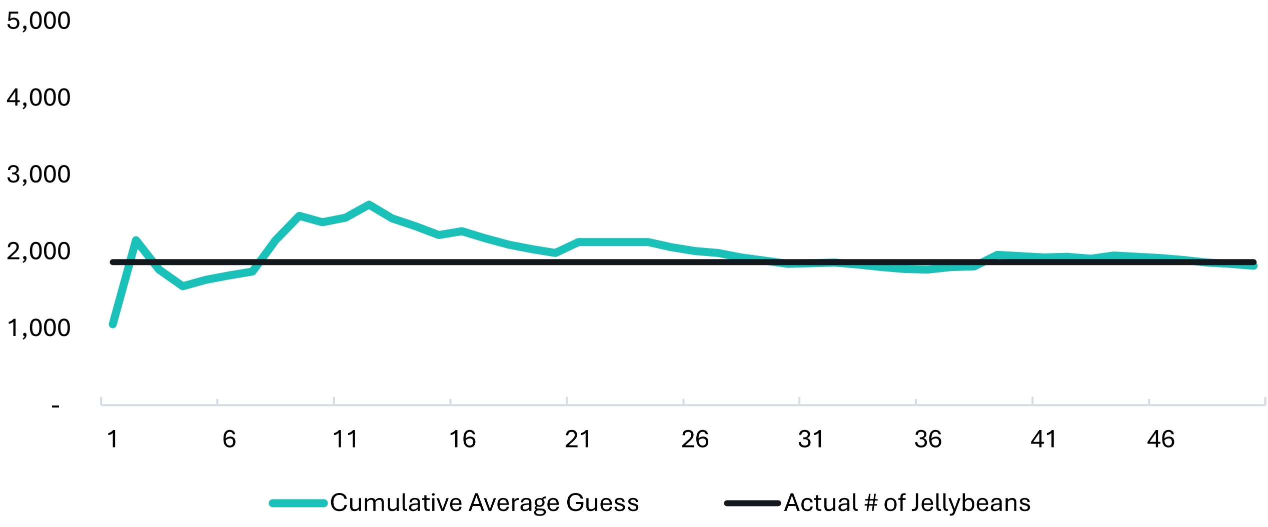
Collective Intelligence is the enhanced capacity for problem-solving, decision-making, and prediction that emerges when multiple independent agents contribute diverse perspectives toward a shared objective.[5] It is often illustrated by the "Wisdom of Crowds" effect – the phenomenon that the average prediction of the group tends to vastly exceed that of any one individual.

The Jellybean Experiment: A Demonstration of Aggregated Accuracy

In April 2025, Savana conducted a classical demonstration of this effect in Martin Place, Sydney. A jar containing exactly 1,863 jellybeans was displayed, and passers-by were asked to estimate the quantity. Responses varied widely, from 300 to 7,803, with an average absolute individual error of 1,107 - a deviation of nearly 60% from the true figure.

But remarkably, the average estimate of the group was 1,803 - within 4% of the actual number. This is because the overestimates and underestimates tend to cancel out, producing an aggregate that converges closely on the true value. Of the participants, only one individual provided a more accurate guess than the group mean.

Figure 1: Average & Actual Estimate (y-axis) versus Number of Estimates (x-axis)



This outcome is not an anomaly. The jellybean experiment has been replicated many times over, consistently demonstrating the predictive validity of aggregated judgement.[6]

[5] Page, S. E. (2007). *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies.* Princeton University Press.

[6] Mauboussin, M. J. (2007, March 20). *Explaining the Wisdom of Crowds: Applying the Logic of Diversity*. Legg Mason Capital Management.

Collective Intelligence as an Emergent Property

Within the framework of Complex Adaptive Systems, Collective Intelligence is best understood as an emergent property arising from the interaction of numerous adaptive agents. In financial markets, millions of heterogeneous actors continuously buy and sell securities in response to evolving information. This activity aggregates dispersed knowledge into prices, yielding highly efficient price discovery.

The Conditions of Collective Accuracy

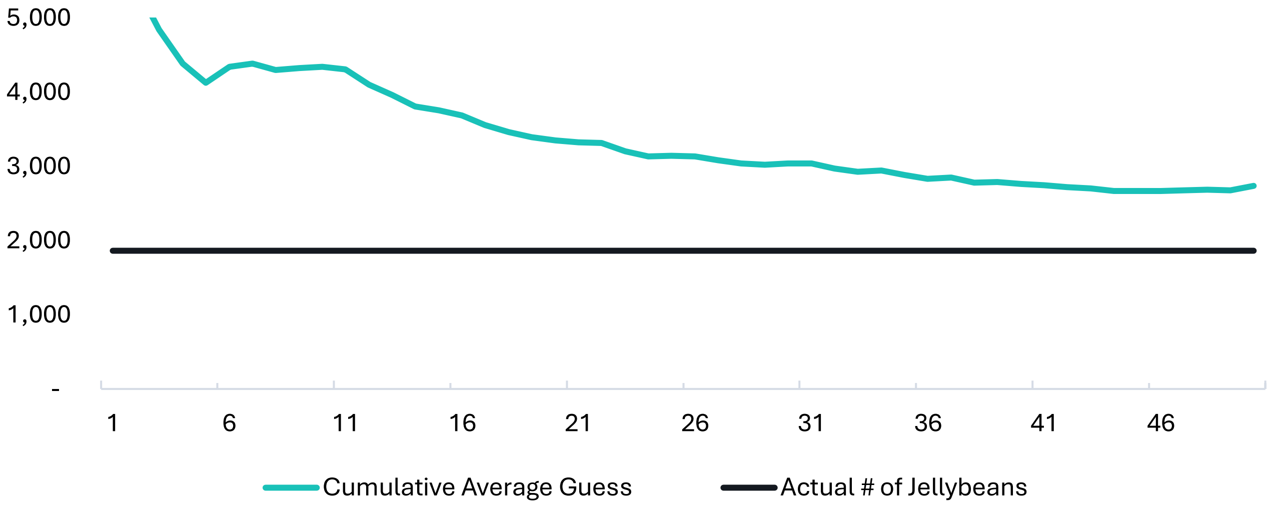
Crucially, however, the efficacy of Collective Intelligence depends upon two key conditions: diversity and independence.[7]

- Diversity requires not only a sufficiently large number of agents but also heterogeneity of perspectives, assumptions, and heuristics. Diversity ensures that errors are uncorrelated and cancel out rather than reinforcing one another.
- Independence requires that each agent form their judgement autonomously, without undue influence from others. This safeguards against correlated errors caused by herding or groupthink.

Violating Independence: A Modified Experiment

In September 2025, Savana repeated the jellybean experiment in Surry Hills, Sydney, but deliberately relaxed the independence condition. Participants were told that there had been two (fake) "prior estimates" of 2,924 and 3,051 respectively, while the actual count remained 1,863.

Figure 2: Modified Experiment: Average & Actual Estimate (y-axis) versus Number of Estimates (x-axis)



[7] Mann, R. P., & Helbing, D. (2017). *Optimal incentives for collective intelligence*. Proceedings of the National Academy of Sciences, 114(20), 5077–5082.

The introduction of these anchors produced a systematic distortion in outcomes. Although the mean absolute error increased only marginally (from 1,107 to 1,179), the average estimate shifted substantially from 1,803 to 2,728 (a 46% error). The result demonstrates that violations of independence generate directional bias, thereby reducing the reliability of collective forecasts.

Figure 3: Side-by-Side Comparison: Original Experiment v Modified Experiment

	Original Experiment	Modified Experiment
Actual Number of Jellybeans	1,863	1,863
Number of Estimates	52	52
Average Absolute Error	1,107	1,179
Average Estimate	1,803	2,728
Error	-3.23%	46.45%

Implications for Financial Markets

These findings carry direct implications for financial markets. While markets often display near-optimal efficiency through the aggregation of diverse and independent perspectives, they are also susceptible to systematic breakdowns when either condition is violated. Herding dynamics, feedback loops, and the influence of irrational behavioural biases ("fear and greed") introduce correlated errors, reducing the efficacy of collective price discovery.

From this perspective, markets may be conceived as "mostly efficient," yet prone to episodic inefficiencies that arise when Collective Intelligence falters. For Savana, this framework represents not merely a theoretical lens but an actionable opportunity: to identify, with systematic discipline, the moments when diversity and independence erode and to exploit the resultant mispricing.

Savana's Collective Intelligence Model

Replicating the Cognitive Diversity of the Market Through Technology

Savana's first-of-its-kind approach reckons with Complex Adaptive financial markets by designing its own synthetic form of Collective Intelligence, engineered to replicate the cognitive diversity of the market within an objective and consistent framework. Achieving the level of breadth and precision required for this challenge is only possible through Savana's proprietary technology platform, which deploys cloud-scale infrastructure to operationalise this process at scale.

At its core, the technology platform ingests vast pools of data, which is systematically transformed into valuation insights. While any single perspective on valuation may be incomplete, the aggregated output of the system converges toward assessments that are more resilient than those generated by isolated methods. In this sense, Savana recreates the "wisdom of crowds" effect inside a disciplined, data-driven process that remains unbiased and uncorrupted by sentiment, feedback loops, or consensus drift.

Crucially, the design of the framework preserves the fundamental principles of diversity and independence - the necessary conditions for reliable collective accuracy. This ensures that each perspective contributes a distinct informational signal to the process, while no single bias or distortion dominates the outcome. The result is a collective prediction mechanism that is stronger, more adaptive, and more consistent than any singular approach.

Ultimately, it is the technology that renders Savana's Collective Intelligence model feasible. By combining large-scale computational power with a disciplined algorithmic framework, the platform delivers both the breadth to evaluate thousands of companies simultaneously and the precision to detect systematic mispricings with statistical rigour. This integration ensures that Savana's process is not only consistent and repeatable, but also scalable across markets and time horizons.

Validation Criteria

To assess the efficacy of Savana's synthetic Collective Intelligence, we apply three evaluative criteria:

1. **General Alignment**: In line with the premise of market efficiency, Savana's valuations should broadly track prevailing market prices.

2. **Selective Divergence**: Discrepancies should be rare and concentrated in market segments with structural inefficiencies.

3. **Predictive Accuracy**: Where divergences occur, Savana's valuations should demonstrate superior forward-looking accuracy relative to contemporaneous prices.

Data and Testing Methodology

Before presenting results, it is necessary to define the testing environment in which Savana's signals are evaluated.

The dataset spans a ten-year period from 1 January 2015 to 1 January 2025, divided into 61 discrete, non-overlapping bi-monthly observation periods. The analysis evaluates the full universe of companies listed in the US (namely on the NYSE and NASDAQ), subject to minimum market capitalisation (US$500m) and liquidity thresholds (equating to approximately 2,400 companies).

For every company in this population, Savana assigns a valuation score between 0 and 1. A score of 0.5 represents intrinsic fair value, with values below 0.5 indicating undervaluation and above 0.5 indicating overvaluation. These scores are not linear measures of mispricing; rather, they represent a probabilistic signal. The further a company's score diverges from 0.5, the greater the implied probability that it's market price deviates from intrinsic value.

To facilitate analysis, valuation scores are grouped into eight evenly spaced buckets (each spanning 2.5 percentage points), with the extreme ends of the distribution broadened to capture all the companies at the tails. This bucketing approach enables a systematic view of valuation distributions over time and provides a basis for evaluating subsequent return performance based on Savana's signals.

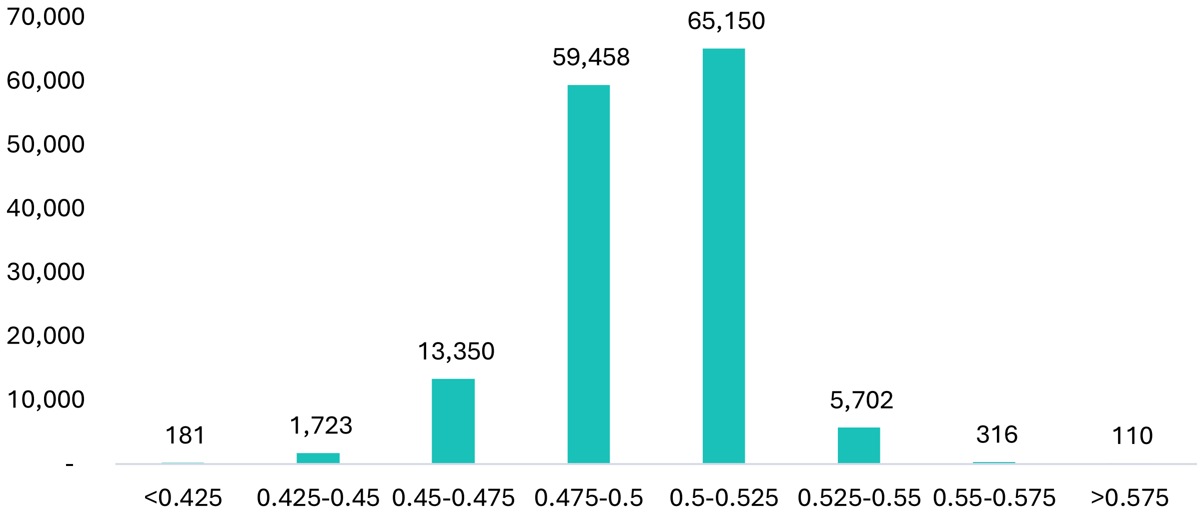
The analysis then evaluates the relationship between Savana's valuation signals and each company's subsequent two-month returns, consistent with the bi-monthly rebalancing frequency of Savana's portfolios. To ensure robustness, return distributions are winsorized (clipped) at the 1st and 99th percentiles, thereby reducing the influence of extreme outliers while preserving the integrity of the underlying performance patterns.

Condition 1: General Alignment

If markets are broadly efficient, prevailing prices should reflect underlying fundamentals with reasonable accuracy. Accordingly, Savana's alternative valuations are expected to exhibit a high degree of correspondence with market prices under normal conditions.

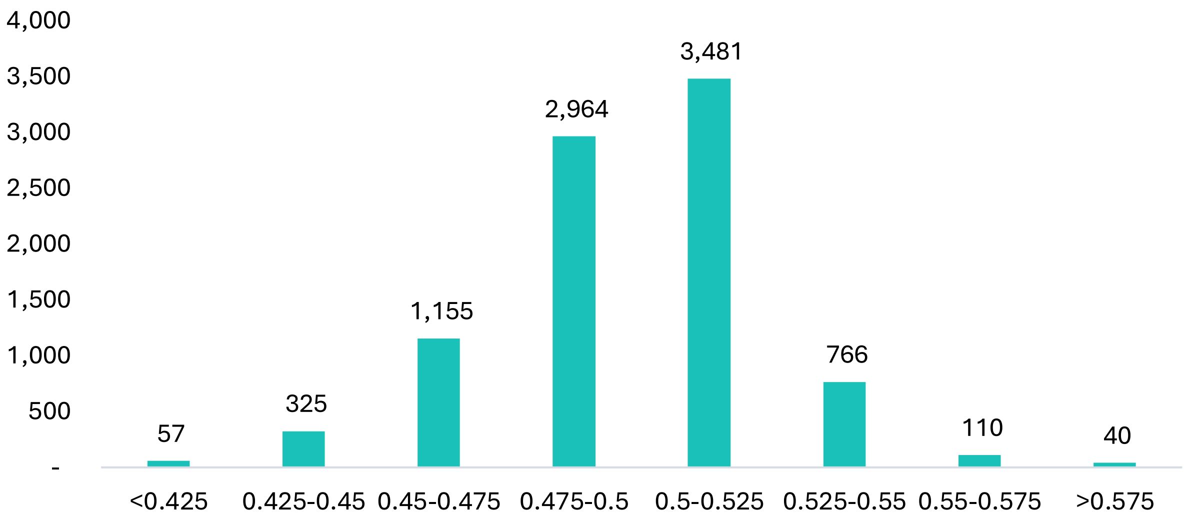
Figure 4 below reports the total company observations in each valuation bucket, while Figure 5 shows the number of distinct companies represented in each bucket.

Figure 4: Savana Valuation (x-axis) versus Total Company Count (y-axis)



Source: Savana, S&P Global. Number of observations = 145,990 (equivalent to an average of ~2,393 companies observed across 61 observation periods).

Figure 5: Savana Valuation (x-axis) versus Unique Company Count (y-axis)



Source: Savana, S&P Global. Number of observations = 8,898 (equivalent to an average of ~2,393 companies. Note that unique companies appear in 3.8 buckets on average over the measurement period).

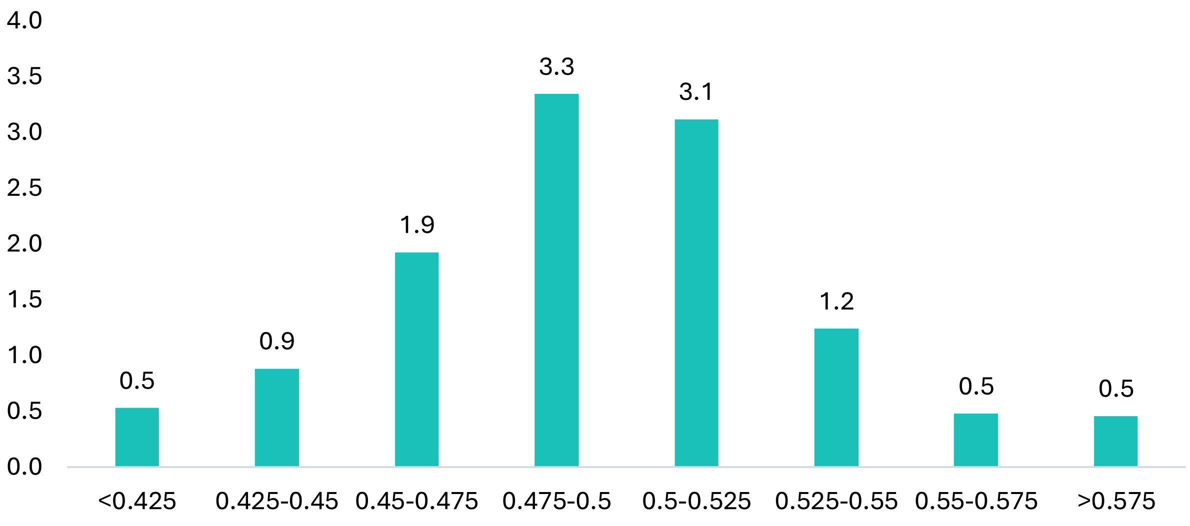
As observed, the vast majority of observations cluster tightly around fair value (0.475–0.525), while only a very small minority occupy the extreme tails of undervaluation or overvaluation. This pattern provides clear evidence that Savana's methodology does not systematically diverge from prevailing prices. Instead, it demonstrates broad alignment with market valuations, validating that Savana's synthetic Collective Intelligence captures the efficiency of the market in aggregate, while still allowing for targeted divergences where inefficiencies arise.

Condition 2: Selective Divergence

The results from Condition 1 implicitly validate Condition 2: although Savana's valuations and market prices are generally aligned, there are rare but notable instances of material divergence at the tails of the distribution.

This is further evidenced by the average duration that a company spends in each bucket. The results show that more "fairly valued" companies typically spend over three years in their specified valuation range, whereas those that fall into the extreme tails (<0.425 or >0.575) remain there for less than half a year on average. In addition, each company on average appears in 3.8 different valuation buckets over the ten-year period. This mobility underscores that most firms do not remain permanently classified as undervalued or overvalued; rather, they migrate across valuation states as perceptions and fundamentals evolve. These findings add a temporal dimension to Conditions 1 and 2: not only are company mispricings uncommon, they also tend to be relatively short-lived.

Figure 6: Savana Valuation (x-axis) versus Average Years Per Company (y-axis)

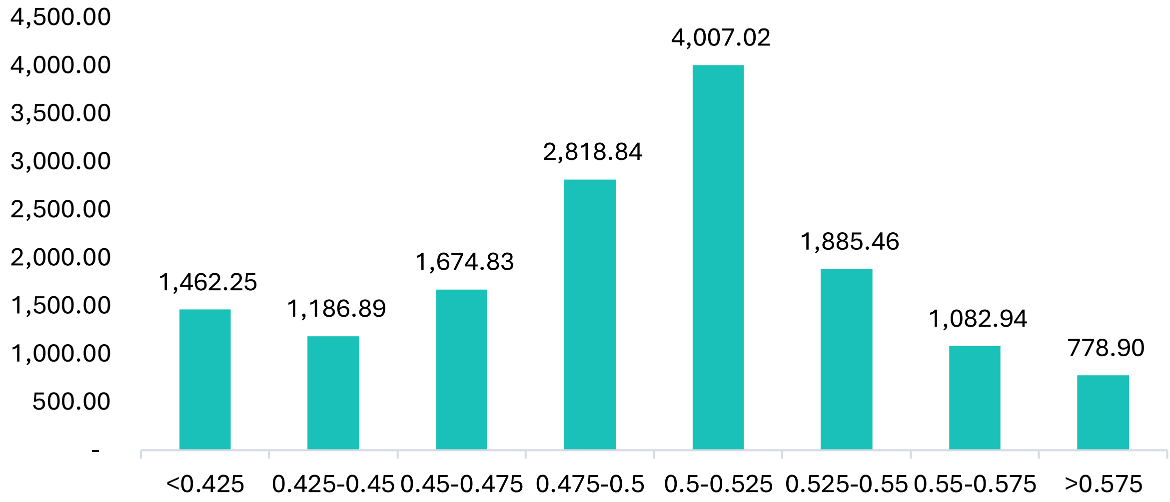


Source: Savana, S&P Global.

Condition 2 further hypothesises that such divergences are not randomly distributed but disproportionately concentrated in structurally inefficient market segments - in particular, smaller companies with lower market capitalisations. These firms are empirically less researched and less widely covered by analysts, which increases the likelihood that pricing inefficiencies persist.

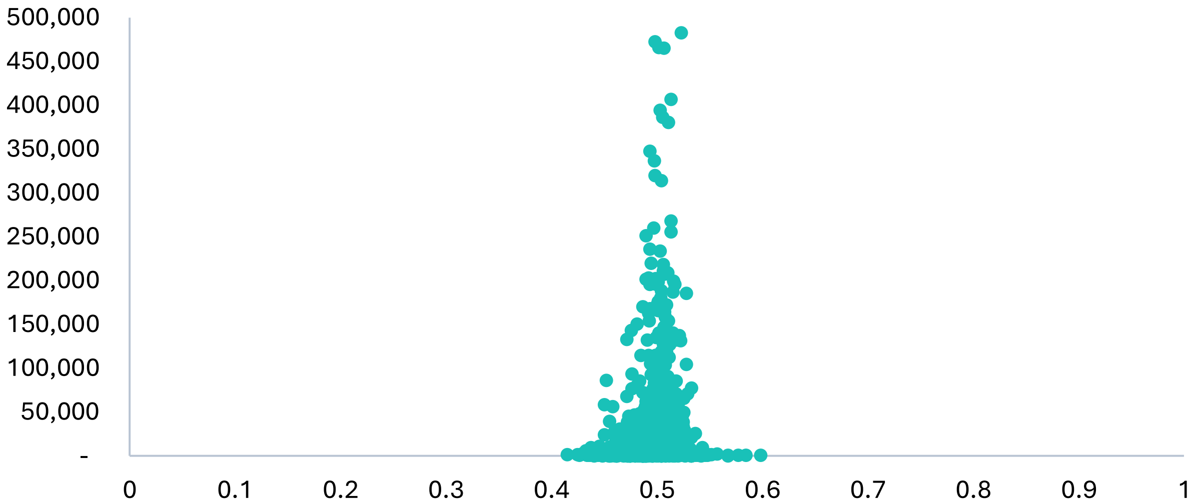
This hypothesis is examined in Figures 7 and 8. Figure 7 plots Savana's valuation buckets against the median market capitalisation over the 10-year measurement period, while Figure 8 shows a scatter plot representing a snapshot of the company data as of 1 January 2025.

Figure 7: Savana Valuation (x-axis) versus Median Market Cap (US$m) (y-axis)



Source: Savana, S&P Global.

Figure 8: January 2025 snapshot of Savana Valuation (ungrouped) (x-axis) versus Market Cap (US$m) (y-axis)



Source: Savana, S&P Global. Snapshot of eligible companies as at 1-Jan-25. (N = 2,517) Y-axis cut-off at US$500bn to improve scale and visibility.

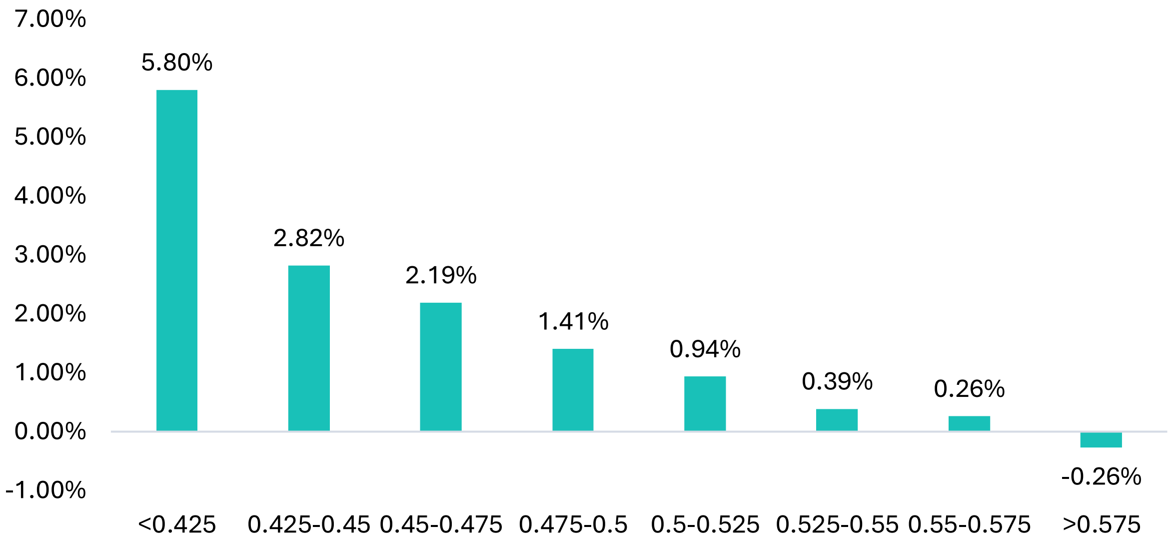
The results show a clear pattern: larger companies cluster tightly around fair value, whereas smaller companies are more frequently represented in the distribution's tails, signalling higher probabilities of mispricing. This distributional evidence supports the hypothesis that material divergences are more likely to arise within the small-cap segment, consistent with the premise of selective inefficiency.

Condition 3: Predictive Accuracy

If Savana's valuations are accurate, then companies assessed as undervalued should, on average, deliver stronger forward returns as prices revert toward fair value, while those assessed as overvalued should underperform. In other words, the ultimate test of validity is whether Savana's valuations possess greater predictive power over future price movements than the market itself.

This test is illustrated in Figure 9, which plots Savana's valuation scores against subsequent average two-month returns over the ten-year period from 2015 to 2025.

Figure 9: Savana Valuation (x-axis) versus Return (%) (y-axis)



Source: Savana, S&P Global. Non-overlapping, bi-monthly returns.

The results resoundingly confirm the hypothesis. Savana's valuation exhibits a highly systematic relationship with subsequent average returns.

The relationship is strikingly linear; a simple regression shows that the coefficient on Savana's valuation is negative and highly significant ($p = 0.0013$), confirming that lower valuations are reliably associated with stronger future performance. Meanwhile, the model produces an R^2 of 0.84, demonstrating that Savana's valuations explain the vast majority of the variation in average two-month returns across the 10-year period. While this highly aggregated regression is helpful in revealing the underlying relationship, the limited number of observations imposes constraints on statistical power. In addition, aggregating to 10-year mean returns reduces cross-sectional variance, which can overstate the apparent strength of the relationship.

To address this, we also perform a complementary time-series test, re-estimating the regression within each of the 61 discrete two-month observation periods and then averaging the results to derive an overall measure of the relationship through time. The results of this analysis are presented below, with the full set of bi-monthly regressions detailed in Annexure 3.

Figure 10: Mean Results from Bi-Monthly Regressions

Observations	Mean Slope	T-Stat	1-tail P-Value	Mean R^2
61	-0.004235	-1.38	0.0865	0.3633

As expected, this test introduces higher variance and reduces the explanatory power of Savana's valuations. Nevertheless, the results remain directionally consistent with the cross-sectional findings and continue to validate the relationship. The average regression slope across all periods is negative (-0.0042) with a t-statistic of -1.38 and a one-tail p-value of 0.0865, indicating that the inverse valuation–return relationship persists across time and remains statistically directional at the 10% level. The mean R^2 of 0.36 further demonstrates that, even when tested independently across multiple market environments, Savana's valuation scores continue to explain a meaningful proportion of subsequent return variation.

Together, these analyses confirm that Savana's valuation framework displays both structural stability and predictive persistence, revealing a consistent, repeatable relationship between valuation and future performance across a decade of distinct market conditions.

Systematic Mispricing Rather Than Cyclical Timing

It is important to emphasise that Savana's valuation model is fully normalised against market cycles. By construction, a company is no more likely to be classified as undervalued simply because the broader market has declined. This ensures that our signals are not driven by cyclical downturns ('buy-the-dip' dynamics) but instead reflect genuine episodes of mispricing that can emerge under any market regime.

This is illustrated in the following regression, which examines the relationship between the frequency of Bucket 1 valuations per observation period and the market return (measured using the S&P 500 index) over time. The analysis shows that while the regression is statistically significant, the explanatory power is modest ($R^2 \approx 0.22$) and the effect size is economically negligible. Importantly, the relationship runs in the opposite direction to what would be expected if performance were driven by buy-the-dip dynamics: undervaluation frequencies tend to rise alongside, not against, positive market returns.

Figure 11: Bucket 1 Frequency v Market Return

Multiple R	0.472057
R Square	0.222838
Adjusted R Square	0.209666
Standard Error	2.591713

Observations	61			
	Coefficients	**Standard Error**	**t Stat**	**P-value**
Intercept	-0.65997	0.942236	-0.70043	0.486413
X Variable 1	0.000526	0.000128	4.113058	0.000123

These results confirm that Savana's model is identifying idiosyncratic mispricings at the stock level, rather than mechanically capturing cyclical downturns, reinforcing the independence and robustness of the valuation framework.

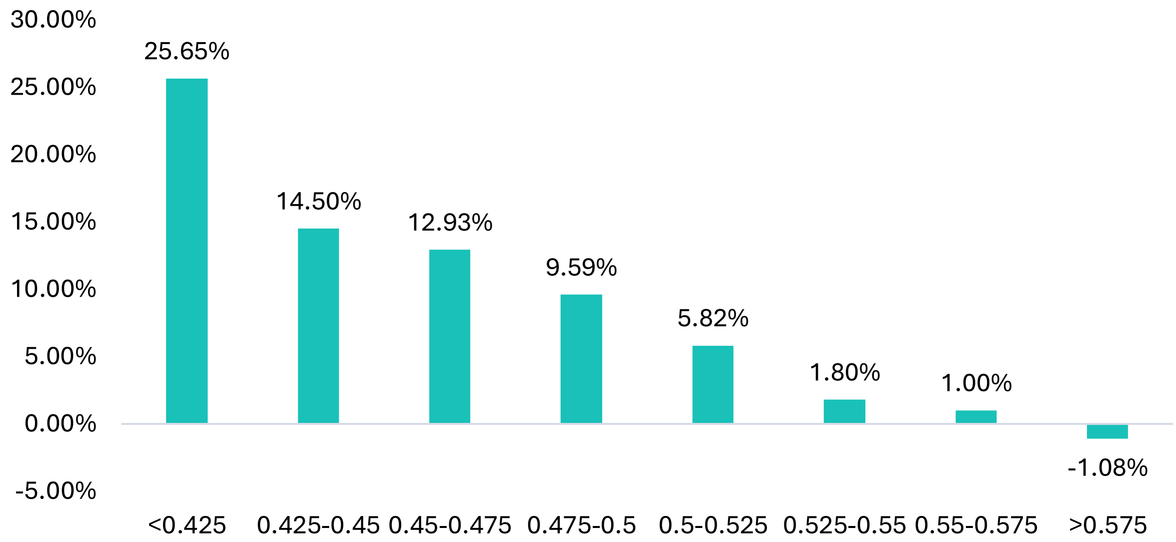
Deconstructing the Returns

Having established that Savana's valuations are broadly predictive of future returns, it is useful to examine the character of those returns beyond headline performance. Through this analysis, we continue to find that the additional parameters – including risk-adjusted outcomes, win rates and upside/downside – support Savana's Collective Intelligence explanation of markets and align with existing empirical market theory.

Risk-Adjusted Returns

The relationship between Savana's valuations and future performance remains robust when evaluated on a risk-adjusted basis, as observed in Figure 12 below.

Figure 12: Savana Valuation (x-axis) versus Risk-Adjusted Return (%) (y-axis)

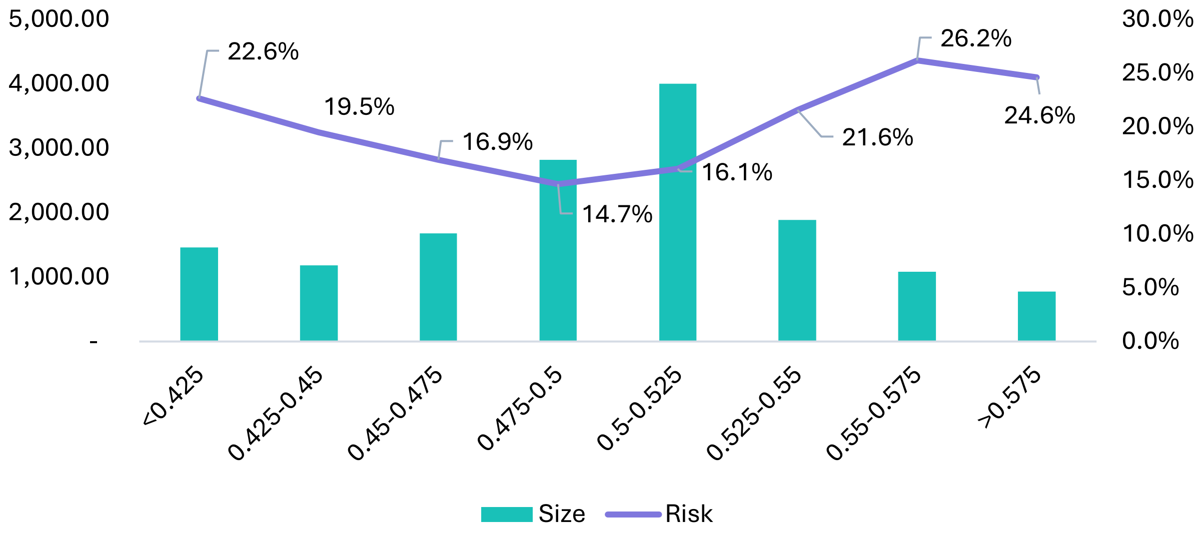


Source: Savana, S&P Global. Based on non-overlapping, bi-monthly risk-adjusted returns data from 1 January 2015 to 1 January 2025. Risk-adjusted return computed as the ratio of the average bi-monthly return to the standard deviation.

Risk

The distribution of risk across Savana's valuation buckets aligns closely with theoretical expectations. As shown in Figure 13, the standard deviation of company price movements traces a U-shaped profile: volatility is lowest near fair value and rises at the extremes. This pattern is intuitive and well-documented - smaller, less efficient companies tend to experience both greater pricing anomalies and higher volatility. The result reinforces the structural relationship between company size, market efficiency, and risk.

Figure 13: Savana Valuation (x-axis) versus Median Market Cap (y-axis (LHS) (US$m)) and Standard Deviation (y-axis (RHS))



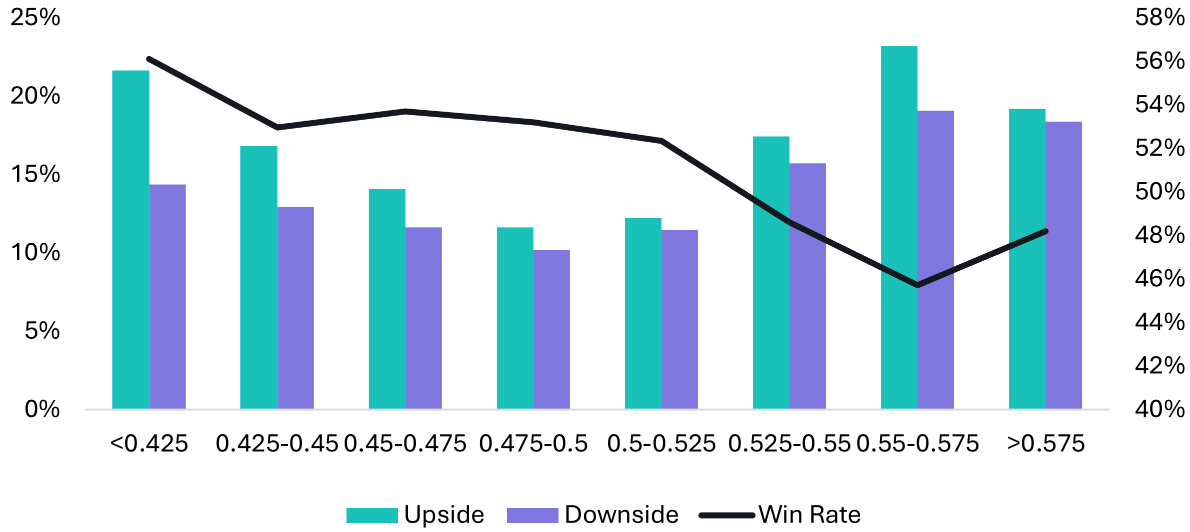
Source: Savana, S&P Global. Size is measured by median market cap. Risk is measured by average standard deviation.

Upside/Downside & Win Ratio

The composition of returns is also consistent with empirical expectations. Smaller companies, where pricing anomalies are more pronounced, exhibit both higher upside potential and greater downside variance. This asymmetry reflects the heightened risk-reward trade-off inherent in less efficiently priced segments of the market. The result is another U-shaped distribution, similar to the distribution of risk observed above. Conversely, the win ratio (the frequency with which returns are positive) follows a more linear pattern, declining as valuations increase.

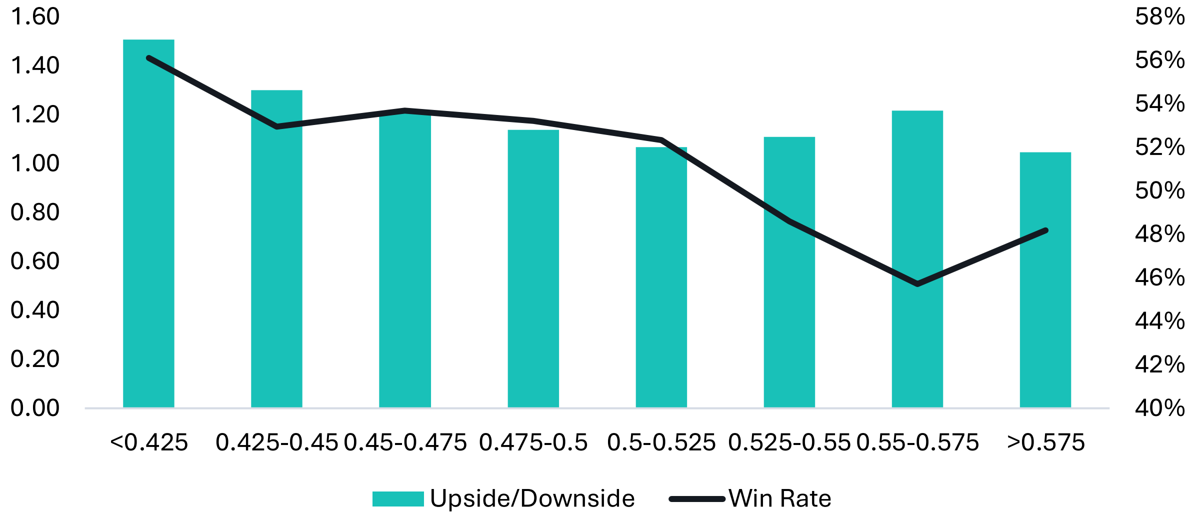
Overall, the higher returns in the more undervalued segments of the market are shown to be driven by a *combination* of higher upside/downside and win rate. These results reinforce two core tenets of Savana's investment philosophy. First, the superior win rate suggests that Savana's framework effectively identifies companies with a higher probability of genuine undervaluation - and, by extension, a higher likelihood of positive performance. Second, the asymmetric return profile observed in these companies supports Savana's thesis that undervalued stocks exhibit risk that is largely priced in, and upside potential that is under-appreciated by the market. Ultimately, this demonstrates how Savana's algorithmic approach systematically exploits these opportunities to capture more upside, more often, while defending capital on the downside - the essence of its asymmetric advantage.

Figure 14: Savana Valuation (x-axis) versus Upside and Downside (y-axis (LHS)) and Win Rate (y-axis (RHS))



Source: Savana, S&P Global. Upside and downside are measured as the average gain and average loss, respectively. Win rate is the ratio of profitable to unprofitable positions.

Figure 15: Savana Valuation (x-axis) versus Upside/Downside (y-axis (LHS)) and Win Rate (y-axis (RHS))



Source: Savana, S&P Global. Upside / Downside is measured as the average gain divided by the average loss. Win rate is the ratio of profitable positions to unprofitable positions.

Conclusion

Framing financial markets as a Complex Adaptive System provides a unifying perspective that reconciles the apparent tension between efficiency and inefficiency. Our application of Collective Intelligence theory explains why markets are generally efficient: the aggregation of independent and diverse participants produces prices that, on average, reflect available information. At the same time, the same framework highlights the conditions under which this mechanism fails. When diversity is constrained, independence compromised, and sentiment-driven behaviours such as fear and greed dominate, efficiency is diminished and mispricings arise.

The empirical evidence presented here is consistent with this framework. Savana's valuations broadly align with market prices, validating the notion of "efficiency most of the time." Yet the systematic clustering of divergences in smaller, less-covered companies confirms that inefficiencies are not only present but also predictable in their locus. Importantly, analysis of forward returns demonstrates that these divergences carry information content: companies assessed by Savana as undervalued tend to outperform, while those flagged as overvalued tend to underperform.

Savana's methodology is designed precisely to capture these opportunities. By engineering a synthetic form of Collective Intelligence through sophisticated technological deployment, we recognise the adaptive efficiency of markets while capitalising on their behavioural breakdowns. In doing so, we systematically position in the under-researched and unpopular segments of the market, where the likelihood of mispricing is greatest.

Overall, the results demonstrate that a disciplined, model-driven replication of Collective Intelligence offers a credible pathway to sustained investment edge. Rather than seeking to deny the efficiency of markets, Savana's approach accepts it as the baseline condition, while focusing systematically on the rare but repeatable instances where efficiency fails. In this sense, the objective is not to outguess the market, but to outperform by consistently recognising and exploiting its predictable mistakes.

Annexure 1 – References

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486

Gabriela, A. (2015). The efficient market hypothesis: Review of specialized literature and empirical research. Procedia Economics and Finance, 32, 442–449. https://doi.org/10.1016/S2212-5671(15)01416-7

Brown, S. J. (2020). The efficient market hypothesis, the Financial Analysts Journal, and the professional status of investment management. Financial Analysts Journal, 76(2), 5–14. https://doi.org/10.1080/0015198X.2020.1735868

Carmichael, T., & Hadžikadić, M. (2019). The fundamentals of complex adaptive systems. In Understanding Complex Systems (UCS). Springer. https://doi.org/10.1007/978-3-030-20309-2_2

Page, S. E. (2007). The difference: How the power of diversity creates better groups, firms, schools, and societies. Princeton University Press.

Mauboussin, M. J. (2007, March 20). Explaining the wisdom of crowds: Applying the logic of diversity. Legg Mason Capital Management. https://doi.org/10.2139/ssrn.909105

Mann, R. P., & Helbing, D. (2017). Optimal incentives for collective intelligence. Proceedings of the National Academy of Sciences, 114(20), 5077–5082. https://doi.org/10.1073/pnas.1618722114

Annexure 2 – Full Dataset Results

Valuation Bucket	Valuation Score Band	Median Valuation	Min Valuation	Max Valuation	Mean Return	Std Return	Median Return	Min Market Cap	Market Cap 25th	Median Market Cap	Market Cap 75th	Max Market Cap	Total Count	Distinct Companies	Wins	Losses	Avg Upside	Avg Downside	Return To Risk	Win Rate	Lose Rate	Win Loss Ratio	Upside Downside Ratio
1	<0.425	0.4169	0.3439	0.4249	0.0580	0.2262	0.0368	515.8706	788	1462	2525	8497	181	57	101	79	0	-0.1437	0.2565	0.5611	0.4389	1.2785	1.5060
2	0.425-0.45	0.4435	0.4251	0.4500	0.0282	0.1946	0.0137	500.2152	729	1187	2829	49192	1723	325	911	809	0	-0.1294	0.1450	0.5297	0.4703	1.1261	1.3006
3	0.45-0.475	0.4673	0.4500	0.4750	0.0219	0.1694	0.0115	500.0034	905	1675	3960	221317	13350	1155	7162	6176	0	-0.1161	0.1293	0.5370	0.4630	1.1597	1.2139
4	0.475-0.5	0.4914	0.4750	0.5000	0.0141	0.1466	0.0089	500.0065	1257	2819	7433	1787053	59458	2964	31612	27798	0	-0.1021	0.0959	0.5321	0.4679	1.1372	1.1385
5	0.5-0.525	0.5081	0.5000	0.5250	0.0094	0.1609	0.0069	500.0062	1536	4007	13166	3785304	65150	3481	34067	31031	0	-0.1148	0.0582	0.5233	0.4767	1.0978	1.0669
6	0.525-0.55	0.5300	0.5250	0.5500	0.0039	0.2158	-0.0058	500.1442	943	1885	5071	481087	5702	766	2768	2928	0	-0.1571	0.0180	0.4860	0.5140	0.9454	1.1086
7	0.55-0.575	0.5572	0.5501	0.5750	0.0026	0.2619	-0.0272	503.6357	662	1083	2436	62010	316	110	144	171	0	-0.1906	0.0100	0.4571	0.5429	0.8421	1.2178
8	>0.575	0.5874	0.5750	0.6917	-0.0026	0.2462	-0.0143	501.7554	625	779	1553	13931	110	40	53	57	0	-0.1837	-0.0108	0.4818	0.5182	0.9298	1.0456

Annexure 3 – Time Series Regression Results

Bi-Month	No. of Observations	Mean Slope	R Squared
01-Jan-15	7	-0.01578989	0.30173317
01-Mar-15	8	-0.030251075	0.650668527
01-May-15	7	-0.020148537	0.23891704
01-Jul-15	6	0.00180149	0.006640567
01-Sep-15	6	-0.052268373	0.858127295
01-Nov-15	6	0.015582536	0.79601395
01-Jan-16	6	-0.008514025	0.14498165
01-Mar-16	7	-0.00433611	0.025374018
01-May-16	7	-0.032905025	0.275609918
01-Jul-16	7	0.001301989	0.020436032
01-Sep-16	6	0.01791286	0.509182876
01-Nov-16	7	-0.027893544	0.818683877
01-Jan-17	7	0.003971715	0.055900967
01-Mar-17	7	-0.009074062	0.191690982
01-May-17	6	0.013075782	0.88629053
01-Jul-17	7	0.035603957	0.621868487
01-Sep-17	8	0.02018904	0.534705787
01-Nov-17	7	-0.030328887	0.359664894
01-Jan-18	7	0.022654971	0.727589209
01-Mar-18	8	0.008854863	0.044387282
01-May-18	7	-0.034597555	0.58939699
01-Jul-18	6	0.018331983	0.501187279
01-Sep-18	7	-0.02117827	0.250842391
01-Nov-18	6	-0.026393581	0.612729159
01-Jan-19	7	0.017751356	0.413772083
01-Mar-19	7	0.018140751	0.551223414
01-May-19	7	0.096663899	0.724328937
01-Jul-19	6	0.026500467	0.754041582
01-Sep-19	7	-0.03669228	0.311450591
01-Nov-19	7	-0.006614246	0.110394268
01-Jan-20	8	-0.002530208	0.00377758
01-Mar-20	8	-0.036485598	0.296891718
01-May-20	7	0.007883929	0.197125823
01-Jul-20	8	-0.020495975	0.275130454
01-Sep-20	8	-0.021173215	0.514593504
01-Nov-20	8	0.012254265	0.125026285
01-Jan-21	8	0.012382245	0.136142264
01-Mar-21	8	-0.020949204	0.202391552
01-May-21	8	0.01757006	0.442837269
01-Jul-21	8	-0.016482208	0.537600737
01-Sep-21	8	0.010706104	0.07679112
01-Nov-21	8	-0.017059138	0.522230372
01-Jan-22	8	-0.024621488	0.580520086
01-Mar-22	8	-0.010638536	0.563177173
01-May-22	8	0.008406736	0.155191751
01-Jul-22	8	-0.000965913	0.001697376
01-Sep-22	8	-0.011596222	0.401870325
01-Nov-22	8	-0.027281586	0.687750062
01-Jan-23	8	-0.003328381	0.023942005
01-Mar-23	8	-0.003443154	0.058183813
01-May-23	8	0.004124302	0.091387817
01-Jul-23	8	0.004158409	0.007533552
01-Sep-23	8	-0.024598298	0.868180194
01-Nov-23	8	-0.010575212	0.437032801
01-Jan-24	8	-0.009335375	0.196337286
01-Mar-24	8	-0.024826256	0.574549426
01-May-24	8	0.035270924	0.433531844
01-Jul-24	8	-0.000754204	0.000511082
01-Sep-24	7	-0.015977149	0.109856484
01-Nov-24	8	-0.041890847	0.331747927
01-Jan-25	8	0.012582964	0.417283467

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IMPORTANT INFORMATION

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