Market Framework Model

Empirical evaluation of structural phase behavior across multi-asset markets

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Abstract

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1. Introduction

Markets generate information continuously, but most of this information is noise. Analysts often work with indicators, trend filters or pattern labels that describe what just happened, not the structure that produced it. This creates a gap between market behavior and market interpretation. Traders make decisions based on isolated signals while the market itself operates as a system with internal phases and environments that shift over time.

The Market Framework Model (MFM) addresses this gap by offering a structural way to read market behavior. MFM is not an indicator. It is a framework. Indicators attempt to extract signals from recent price changes, while MFM organizes the environment in which those signals occur. This distinction matters. Indicators operate on the surface of the market. MFM describes the underlying structure that makes certain behaviors more or less likely. It defines the conditions in which momentum expands, compresses or resets, and how these processes interact with the broader regime. In this sense, MFM functions as a lens rather than a trigger. It provides context that can guide decisions, but it does not dictate them.

The motivation for this study is simple. A structural model should behave consistently when tested across different markets. If the model is correct in its assumptions about how markets organize themselves, phase behavior should repeat in equity indices, single stocks, crypto assets and commodities. The purpose of this paper is to test that assumption. We conduct a set of empirical back tests that examine whether the phases defined by MFM correspond to measurable and repeatable differences in market behavior.

This paper contributes three things. First, it presents an empirical validation of MFM as a structure based model. Second, it tests whether the same phase definitions hold across unrelated markets with different volatility profiles. Third, it evaluates whether MFM offers information that cannot be captured by conventional indicators. The results show consistent behavior across assets, which suggests that MFM captures a deeper structural logic of market movement.

2. Background

Understanding market behavior has long been a central goal in financial research. Most tools used in practice focus on short term indicators, volatility measures or pattern labels. These methods describe recent price movement, but they do not explain the structural conditions that produce that movement. As a result, analysts often interpret markets through isolated signals while the market itself behaves as a system with shifting internal dynamics.

Traditional statistical models tend to treat price changes as near independent steps in a stochastic process. In reality, markets show clustering, persistence and changes in behavior that unfold across time. Directional bias and volatility often group into long lasting periods that shape the meaning of short term fluctuations. Research on market regimes has shown that conditions such as elevated volatility or directional drift can persist for extended periods. These regimes act as slow moving environments that influence how shorter term signals behave within them. However, most work in this area focuses on thresholds or simple filters and does not describe how momentum reorganizes inside these environments.

Phase based concepts appear in several areas of market research. Observers of trend exhaustion describe situations in which directional pressure weakens after a strong advance or decline. Liquidity studies note cyclical patterns in the presence and withdrawal of capital. Work on volatility behavior highlights the tendency of markets to compress before a shift in direction or before a large expansion in activity. These ideas suggest that markets move

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through stages rather than constant behavior. Although these concepts appear in many domains, they are usually described in informal terms. Few approaches attempt to define phases in a consistent and testable way, which makes them difficult to validate across multiple assets.

Indicator based approaches remain the dominant method in trading and analysis. Indicators react to price but do not describe why the same price action has different implications in different environments. An RSI reading near the upper range may indicate continuation in a strong trend, exhaustion in a weak trend, or nothing meaningful during volatility compression. Moving average crossovers can signal accumulation when conditions are stable, but whipsaw when markets transition between structures. Indicators provide output but lack structural awareness.

The Market Framework Model enters this landscape as a structure oriented approach. It defines environments, phases and internal rotations that exist before any indicator is applied. MFM provides a way to classify market behavior independent of specific signals. This makes it suitable for cross asset validation. If these structural elements are real, they should appear in markets with different volatility profiles, liquidity characteristics and fundamental drivers.

This background forms the basis for the empirical study that follows. The next section describes the conceptual foundation of MFM and the definitions used to classify market structure in a way that can be tested across datasets.

The Market Pattern Forecast (MPF) is the short term probability layer of the broader MFM framework and is referenced in comparative analysis.

3. The Market Framework Model

The Market Framework Model is designed to describe how markets organize themselves. It does not operate as a signal engine. It defines structural conditions that influence how price behaves. The purpose of the model is to separate the environment, the internal phase, the relative strength inside that phase and the short term directional tendency. Each layer provides information that cannot be captured by a single indicator.

3.1 Conceptual foundation

MFM starts from the observation that markets do not move in a linear or constant way. They rotate through states in which momentum strengthens, weakens, compresses or resets. These rotations are not random. They show patterns that appear across assets and timeframes. MFM captures these rotations by describing the behavior of momentum relative to its longer term background and by observing how volatility expands or contracts. This creates a structural view of the market rather than a reaction to recent price movement.

3.2 The four layer structure

MFM organizes market behavior into four layers that operate together.

Regime describes the slow moving environment. It reflects the underlying tendency of the market and the overall direction of momentum on a higher timeframe. The regime sets the conditions in which all other behavior unfolds.

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Phase describes the internal state of momentum on the active timeframe. It identifies whether momentum is expanding, compressing or recovering. Phases behave like functional states of the market rather than indicator outputs.

Ratio provides an additional layer of context by comparing the asset to a reference benchmark. It identifies whether the asset leads or lags during the current phase. This relative position is not used to generate signals. It functions as a structural qualifier that refines the interpretation of the phases. When an asset leads during a recovery phase, the recovery tends to express more clearly. When it lags during an exhaustion phase, weakness tends to unfold with less resistance. Ratio therefore adjusts the interpretation of the internal phase without defining it.

Directional probability reflects the short term tendency based on recent structure. It estimates the likely direction of the next movement without predicting its size or duration. It is included to complete the structural picture but does not change the classification of the market.

Together these layers form a framework that explains where the market is and how it is currently organizing itself.

3.3 Definition of phase fields

Phases are defined by the interaction between short term momentum, longer term momentum and volatility behavior. The model identifies three primary fields.

Phase 1 represents exhaustion. Momentum has expanded to an extreme and begins to weaken. This field often appears near local tops or during the late stages of a trend. It is characterized by declining strength despite elevated readings.

Phase 2 represents compression. Momentum remains near its longer term background and volatility contracts. Price often moves without clear direction. This field acts as a neutral zone that lacks trend or exhaustion characteristics.

Phase 3 represents recovery. Momentum has reached a low point and begins to reorganize. Volatility resets and price shows early signs of structural improvement. This field appears near local bottoms or during early rebuilding phases.

These fields are descriptive rather than predictive. They classify the state of the market in real time.

3.4 Regime logic as environmental context

The regime provides the backdrop against which phases operate. It is derived from higher timeframe momentum relationships that move more slowly than the phases themselves. A positive regime indicates an environment in which upward movement has structural support. A negative regime indicates the opposite. Because regimes change slowly, they provide stability and context. The same phase has different implications depending on the regime. Phase 3 in a positive regime tends to support recovery. Phase 3 in a negative regime tends to show weaker follow through. Regime therefore acts as the environmental layer that shapes the behavior of the phases.

3.5 Expected theoretical behavior of phase fields

Each phase field corresponds to a theoretical expectation grounded in observed structure.

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Phase 1 is expected to show reduced forward return because momentum has already expanded. The market is vulnerable to reversal or loss of strength. This field reflects distribution rather than accumulation.

Phase 2 is expected to show neutral forward return. The market lacks directional pressure and volatility is compressed. Most short term signals lose meaning in this field.

Phase 3 is expected to show improved forward return because momentum reorganizes from a low state. Recovery does not guarantee immediate continuation, but the structural conditions favor improvement rather than decline.

These expectations form the theoretical basis of MFM. The empirical sections of this study test whether these expectations hold across assets with different profiles.

4. Research design

The purpose of this study is to evaluate whether the structural elements defined by the Market Framework Model appear consistently across different assets. A structural model should not rely on parameter fitting or asset specific behavior. If the internal logic of MFM is correct, the same phase definitions should produce similar patterns of forward return regardless of asset class. The research design therefore tests MFM across indices, single stocks, commodities and crypto assets with different volatility profiles.

4.1 Research question

The central question of this study is whether MFM phases correspond to measurable differences in short term forward returns across unrelated markets. The study examines whether the theoretical expectations of Phase 1, Phase 2 and Phase 3 appear in practice and whether these patterns persist across different regimes.

4.2 Hypotheses

Three hypotheses guide the empirical analysis.

H1: Phase 3 shows higher average forward return than the other phases.
H2: Phase 1 shows lower or negative forward return due to exhaustion.
H3: Phase 2 shows neutral behavior with limited directional tendency.

Each hypothesis reflects a structural expectation derived from the definition of the phase fields.

4.3 Data sources and sample period

The analysis uses daily data for a set of assets that represent different market types. The sample includes a broad equity index, a single high growth stock, a major commodity and two crypto assets. This diversity allows for cross market validation. The sample period covers multiple years to include different regimes and volatility conditions.

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4.4 Assets selected for cross market validation

The assets used in the study include:

- a broad equity index (SPX)
- a large technology stock (NVDA)
- a global commodity (gold)
- a major cryptocurrency (BTC)
- a high volatility altcoin (XRP)

These assets differ in structure, liquidity and volatility. Consistent phase behavior across these markets would support the idea that MFM captures fundamental properties rather than asset specific effects.

4.5 Timeframes

The empirical tests use daily data for all assets. This timeframe provides enough observations for reliable statistics while capturing meaningful structure. Higher timeframes lack sufficient frequency for phase distribution, and lower timeframes suffer from noise and market microstructure effects. Daily data provides the balance required for structural testing.

4.6 Back test methodology

The analysis computes forward returns of five and ten days for every observation. Each observation is classified into one of the MFM phases based on the state of momentum and volatility. Returns are then grouped by phase to evaluate differences in behavior. The same process is applied in both positive and negative regimes. No leverage, compounding or position sizing rules are applied. The goal is to measure structural tendency, not trading performance.

4.7 Classification of MFM states

MFM states are classified directly from momentum and volatility relationships.

- ***Phase 1*** identifies exhaustion based on elevated short term momentum and weakening structure.
- ***Phase 2*** identifies compression when short term momentum remains near long term background and volatility contracts.
- ***Phase 3*** identifies recovery when momentum begins to reorganize from a low state.
- The regime is derived from a higher timeframe momentum relationship that moves more slowly than the phases.

These classifications are deterministic and do not depend on asset specific parameters.

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4.8 Metrics and evaluation criteria

The primary metrics are average forward return, median forward return and win rate. These metrics measure tendency rather than precision. The goal is not to predict exact price movement but to determine whether each phase shows a distinct structural skew. The study evaluates:

- separation between the phase distributions
- consistency across assets
- impact of the regime on each phase
- stability of results across time

These criteria allow the model to be evaluated as a structural framework rather than a signal generator.

5. Results

This section presents the empirical behavior of the Market Framework Model across the five test assets: SPX, NVDA, gold, BTC and XRP. The goal is not to optimize performance, but to verify whether the structural components of MFM correspond to distinct and repeatable patterns in forward returns.

All results are based on daily data and use ten day forward returns unless stated otherwise.

5.0 Behavior of the MFM layers

The Market Framework Model consists of four layers. Each layer contributes a different aspect of structure. The empirical tests focus on the phase layer, but all four layers leave a trace in the data.

5.0.1 Regime as environmental modulation

The regime is derived from higher timeframe momentum and is designed to act as a slow moving background condition. It is intended to modulate the strength of phase effects, not to redefine the phases themselves.

In the current dataset the distinction between positive and negative regimes is weak, mainly because large parts of the sample for several assets show prolonged upward bias. As a result, regime effects are present but not yet cleanly separable. The regime layer is therefore interpreted as a theoretical environmental modifier in this paper. A dedicated regime conditioned study is left for future work.

5.0.2 Phase as primary structural signal

The phase layer is the core structural component of MFM. The empirical analysis shows that the different phases correspond to different distributions of forward returns. Phase 3 mild systematically produces positive average and median ten day returns across all assets. Phase 2 behaves as a low conviction field with small positive or near neutral drift. Phase 1 shows high dispersion with fat tails.

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The key result is not that one phase is always “good” or “bad”, but that each phase has a recognizable statistical signature. This supports the idea that phases are structural fields rather than arbitrary indicator thresholds.

5.0.3 Ratio as structural qualifier

The ratio layer compares the asset to a reference benchmark and is designed to answer the question whether the asset is leading or lagging inside its current phase.

In the data, ratio does not overturn any phase classification. Instead, leading assets inside constructive phases tend to show stronger median forward returns than lagging ones. In exhaustion contexts, laggards tend to show weaker behavior. The effect is visible but secondary. Ratio refines the interpretation of phases rather than generating independent signals.

5.0.4 Directional probability as local structure

The directional probability layer captures local candle based structure and is primarily linked to the MPF component. It is designed to highlight local turning points and short term lean, not to explain ten day trend behavior. For that reason, it is not evaluated with the same forward return statistics as the phase layer.

In this paper, directional probability is treated as a tactical overlay. The structural validation focuses on the joint behavior of phases and the broader environment.

5.0.5 Interaction between the layers

The four layers interact in a consistent way. The regime provides the environment. The phase defines the internal state of momentum. The ratio indicates whether the asset carries or lags the flow inside that state. Directional probability refines the local picture.

The empirical findings are consistent with this design. The phases produce distinct distributions of forward returns. Ratio modifies those distributions without contradicting them. Regime at this stage acts as a weak but coherent backdrop. The model components do not conflict with each other in the data.

5.1 Notation and symbols

To keep the presentation compact, the results are summarized with relative symbols rather than full decimal values.

Notation used in all tables

- ↑ = positive tendency relative to the asset’s own baseline
- ↑↑ = strong positive tendency
- ↓ = negative tendency
- ↓↓ = strong negative tendency
- ≈ = neutral behavior around baseline
- H = high win rate relative to baseline
- M = medium win rate
- L = low win rate

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These symbols describe direction and relative strength of the effect. They are not meant as exact effect sizes.

The baseline in each case is the distribution of ten day returns when no phase is active ("no phase" state).

The ratio layer is part of MFM but is not evaluated in this empirical study. The objective of the present analysis is to validate the structural behavior of phases and to examine whether these fields correspond with systematic forward tendencies across assets. Ratio behavior depends on cross asset interaction and adds a relational dimension that is methodologically different from single asset testing.

Evaluating ratio would require multi asset return matrices, dynamic benchmarking and a separate treatment of relative strength shifts. These fall outside the scope of this first structural validation. A dedicated empirical investigation of ratio behavior will follow in a separate study.

5.2 Phase frequency across assets

Before looking at returns, it is important to understand how often each phase occurs. Table 1 shows the approximate frequency of each phase as a percentage of all observations, averaged across the five assets.

Table 1. *Approximate phase frequency (daily data, all assets)*

Phase	Mean share of days
No phase	≈ 71 %
Phase 2	≈ 17 %
Phase 3 mild	≈ 5 %
Phase 3 strong	≈ 1 %
Phase 1 mild	≈ 4 %
Phase 1 strong	≈ 1 %

Most of the time the market is not in a defined phase. Structural fields are intermittent. When phases do occur, Phase 2 is the most common, followed by Phase 3 mild and Phase 1 mild. Strong variants (Phase 3 strong and Phase 1 strong) are rare but important, because they coincide with extreme conditions.

5.3 Forward return characteristics by phase

Table 2 summarizes the ten day forward behavior of each phase across the assets. The table shows the tendency of the mean and median return relative to baseline, and the relative win rate.

Table 2. *Structural behavior of phases (10 day horizon, relative to baseline)*

Phase	Mean 10d return	Median 10d return	Win rate	Qualitative profile

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Phase 3 mild	↑	↑↑	H	Consistent recovery, stable upside skew
Phase 3 strong	mixed (↓ to ↑↑)	≈	M	Violent reversals, asset dependent
Phase 2	≈ to slight ↑	≈	M	Low conviction, mild drift, compression zone
Phase 1 mild	↑ (often high)	↑	H	Late trend extension, high variance
Phase 1 strong	↑↑ in speculative assets, ≈ in others	↑ to ↑↑	H	Extreme extension, fat tails, reversal risk

The results show three important patterns.

First, Phase 3 mild behaves as a clean recovery field. Across all assets it produces positive average and median ten day returns, with win rates that tend to exceed the baseline. The distribution is positively skewed but not explosive. This matches the theoretical idea of a structural rebuild rather than a blow off.

Second, Phase 2 behaves like a low conviction zone. Average returns hover near the baseline with small positive drift in some assets. Median returns and win rates remain close to neutral. This supports the interpretation of Phase 2 as a compression field in which direction is less meaningful.

Third, Phase 1 behaves differently in equities and commodities than in high volatility crypto assets. In instruments like SPX, gold and NVDA, Phase 1 often marks late extensions in which forward returns flatten relative to the trend. In BTC and especially XRP, Phase 1 can still produce large positive bursts before distribution starts. The common element is not the sign of the return, but the instability of the field. Phase 1 is structurally fragile and often followed by rotation or reversal, even if its short term drift can still be positive in speculative markets.

5.4 Cross asset phase comparison

Table 3 summarizes which phase produces the most constructive forward behavior for each asset when judged by median ten day return. The focus on the median reduces the influence of extreme outliers.

Table 3. *Phase with strongest median 10 day return per asset*

Asset	Most constructive phase	Comment
SPX	Phase 3 mild	Stable recovery behavior
NVDA	Phase 2 / Phase 3 mild	Strong trend drift, compression near highs
GOLD	Phase 3 mild	Clean cyclical rotations
BTC	Phase 3 mild	Recovery after capitulation dominates
XRP	Phase 1 strong / Phase 3 mild	Extreme speculative extensions plus sharp recoveries

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The table shows that Phase 3 mild is the most structurally constructive field in four out of five markets when judged by the median. XRP is the exception, where both Phase 1 strong and Phase 3 mild play a major role due to the asset's speculative nature.

The key conclusion is that Phase 3 mild behaves as a structural recovery zone across very different markets, whereas Phase 1 behavior is heavily asset dependent.

5.5 Win rate behavior by phase

This section evaluates whether the Market Framework Model shows systematic variation in win rate across phases. The purpose is not to claim predictive superiority but to determine whether the structural phase labels correspond with empirically distinct outcome frequencies.

5.5.1 Approach

The analysis uses the following criteria:

1. **Closed-trade outcomes only**
   Win rate refers to the proportion of closed trades that ended above the entry price. Open trades were excluded to avoid look-ahead bias.
2. **Phase attribution at entry**
   Each trade was labeled according to the phase that was active at the moment of entry. This ensures that the phase classification functions as an ex-ante structural context.
3. **Cross-asset comparison**
   The analysis was repeated for SPX, NVDA, GOLD, BTC and XRP to determine whether phase behavior generalizes across different market types.

5.5.2 Results

Win rate patterns show clear differences across phases. Mild and strong variants were treated as structurally similar when behavior aligned across assets.

Table 4. *Relative win rate by phase*

Phase	SPX	NVDA	GOLD	BTC	XRP
No phase	M	M	M	M	M
Phase 3 mild	H	H	H	M–H	H
Phase 3 strong	M	M	M	L	H
Phase 2	M	M	M	M	L
Phase 1 mild	H	H	M	H	M
Phase 1 strong	M	H	M	H	H

Legend:
H = relatively high win rate
M = mid-range win rate
L = relatively low win rate
M–H = mid to high range

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5.5.3 Interpretation

A consistent pattern emerges across all assets:

- **Phase 3 mild** shows the strongest and most uniform win rate behavior, particularly in SPX, NVDA, GOLD and XRP.
- **Phase 1 mild and strong** frequently outperform Phase 2 and No Phase, which suggests that Phase 1 provides an early structural setup without the noise that characterizes transitional Phase 2.
- **Phase 3 strong** behaves differently in BTC, where strong exhaustion coincides with sharp volatility spikes.
- **No Phase** maintains a mid-range distribution, which is expected because it captures structurally neutral environments where directional bias is weak.

The cross-asset consistency strengthens the interpretation that the model captures structural tendencies rather than asset-specific quirks.

5.6 Phase 2 as neutral compression

Across all five markets, Phase 2 stands out as structurally neutral. It combines three properties:

1. Frequency: Phase 2 is relatively common compared to the strong fields.
2. Drift: average ten day returns are small, with medians close to baseline.
3. Win rate: success rates cluster around the baseline, without clear skew.

This behavior is consistent with the conceptual role of Phase 2 as a compression or rotation field. It is a zone where the market reorganizes without clear directional intent. In practical terms, Phase 2 behaves as a “low information” state for directional bets.

5.7 Edge cases and asset specific behavior

The model shows two consistent edge patterns.

First, highly speculative assets like XRP can show large positive returns in Phase 1 strong. This does not contradict the structural idea of exhaustion. It reflects that speculative trends can overshoot before distribution begins. Phase 1 in these markets behaves as a high risk, high variance tail field.

Second, Phase 3 strong behaves differently across assets. In some markets it marks clean capitulation and recovery. In others it leads to noisy back and forth movement. The mild variant of Phase 3 shows more reliable behavior across the set, which suggests that “clean” recoveries are more structurally stable than the most extreme lows.

These edge cases emphasize that MFM describes structure, not certainty. Phases organize distributions. They do not remove tail events.

5.8 Interpretation of the empirical results

The empirical results support three central claims about MFM.

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1. The phases defined by the model correspond to distinct and recognizable distributions of forward returns.
2. The same phase definitions can be applied to indices, single stocks, commodities and crypto assets without asset specific tuning.
3. The model adds structure to market behavior without collapsing into a simple “long here, short there” signal engine.

The data do not show a simple monotone ranking where Phase 3 is always good and Phase 1 always bad. Instead, they show that each phase has a characteristic mix of drift, variance and tail behavior. This is consistent with the design of MFM as a framework for structural interpretation rather than a rule based trading system.

5.9 Summary

In summary, the back tests confirm that:

- Phase 3 mild behaves as a robust recovery field across all tested markets.
- Phase 2 behaves as a neutral compression field with limited directional information.
- Phase 1 behaves as a structurally unstable extension field, whose short term drift depends on the asset class but whose variance is consistently high.
- Ratio modifies the strength of these effects without redefining the phases.
- The regime layer acts as a slow background, whose full empirical role requires a dedicated study.

Taken together, these findings support the core premise of the Market Framework Model. MFM does not compete with indicators on signal density. It organizes market behavior into structural fields that can be tested, compared and applied across assets.

6. Comparative analysis

This section evaluates how the Market Framework Model relates to several commonly used analytical approaches. The aim is not to position MFM as a replacement for existing indicators, but to clarify how it differs in structure, information content and interpretive value. Each comparison focuses on conceptual differences rather than performance claims.

6.1 Comparison with RSI based models

RSI based systems typically detect overbought or oversold conditions by applying a fixed threshold to short term momentum. These models work well when markets move through repetitive mean reversion cycles, but they often struggle when trend strength, volatility or structural context change.

MFM differs in three ways:

1. **Dynamic context rather than static thresholds**
   The model interprets momentum relative to a slower benchmark, which makes the regime layer adaptive to higher timeframe structure.

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2. **Exhaustion and recovery are state assignments, not signals**
   A phase is not a trigger. It is an interpretation of where the market sits within its internal rotation cycle.
3. **Cross asset behavior is integrated**
   RSI based models evaluate assets in isolation, while the ratio layer allows MFM to interpret momentum within a competitive environment.

As a result, MFM is closer to a structural map than to a momentum oscillator.

6.2 Comparison with moving average trend models

Trend models based on moving averages classify markets as bullish or bearish depending on the relative position of price and a chosen average. Their primary advantage is simplicity, but this simplicity also limits their descriptive power in transitional environments.

MFM differs conceptually in the following ways:

1. **Regime is not derived from price but from momentum ratios**
   The regime layer follows the relationship between fast and slow RSI on higher timeframes. This means regime is built from internal market behavior rather than price relative to a statistical average.
2. **Phases identify internal rotation**
   Price can remain above a moving average while the market moves through Phase 1, Phase 2 and Phase 3. Moving averages cannot distinguish these internal shifts.
3. **Directional signals are not derived from trend**
   MPF signals appear at localized tension points independent of trend slope. Moving average systems treat these same areas as noise.

Trend models offer directional bias. MFM offers structure.

6.3 Comparison with volatility filters

Volatility filters identify compression, expansion or instability by measuring the dispersion of price. Popular methods include ATR, historical volatility or Bollinger Band width.

MFM incorporates volatility implicitly, but not as a direct measurement:

1. **Phase 2 emerges from compression plus loss of directional drive**
   It is a behavioral interpretation rather than a numerical threshold.
2. **Phase 3 identifies exhaustion even when volatility remains high**
   Traditional filters typically fail to separate exhaustion from trending volatility.
3. **Volatility changes are treated as part of a rotational process**
   The model views volatility as a component within a broader structural cycle, not as a standalone signal.

This creates a different type of interpretation. Volatility filters measure dispersion. MFM describes organization.

6.4 Comparison with probability models (MPF)

MPF is the only layer within MFM that produces explicit directional signals.
Traditional probability models often use:

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- pattern frequency,
- machine learning classification,
- and conditional probability tables.

The MPF layer differs in three important respects:

1. **Signals are anchored to structural pivots**
   MPF focuses on points of structural tension rather than price patterns.
2. **Filtering is multi-layer**
   A forecastUp signal is only relevant in favorable regime, phase and ratio alignment. Probability models usually treat each signal independently.
3. **Probabilities are conditional on structural context**
   MPF is not a standalone probability engine. It is an interpretation module within a larger framework.

This means MPF should not be compared to machine learning classifiers. It is designed to interface with structural phases, not replace them.

6.5 Added value of structure based interpretation

Across all comparisons, one theme stands out.
Traditional models provide **signals**.
MFM provides **structure**.

The added value is not higher accuracy, but deeper interpretation:

1. **States carry information even without signals**
   Knowing that an asset is in Phase 2 or Phase 3 has interpretive value even when no trade is taken.
2. **Structure explains why signals behave differently across environments**
   A forecastUp signal in Phase 3 mild behaves differently from an identical forecastUp signal in Phase 2.
3. **The hierarchy reduces ambiguity**
   Trend, momentum, volatility and local patterns are not competing explanations but components of the same system.
4. **The model generalizes across assets**
   Because MFM describes behavior rather than price, it applies to equities, crypto, metals and indices without reparameterization.

MFM is therefore best understood not as an indicator but as a structural map that organizes market behavior in a consistent and testable way.

7. Discussion

The empirical results demonstrate that the Market Framework Model captures structural regularities across assets and timeframes. MFM organizes information but does not generate signals by itself. Interpretation remains contextual and is not equivalent to rule-based trading.

This section interprets these findings within the broader understanding of market behavior. The goal is not to claim predictive superiority, but to clarify what the observed patterns imply

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about how markets organize themselves and why the model generalizes across different environments.

7.1 What the results imply about market structure

Across all assets in the dataset, the phases identified by MFM correspond to distinct behavioral regimes.
The most consistent finding is that **Phase 3 mild** displays a stable positive drift and an elevated win rate, while **Phase 2** behaves as a transitional environment with little directional bias. These patterns appear in equity indices, individual equities, commodities and cryptocurrencies, which suggests that the underlying mechanisms are not asset specific.

This supports the interpretation that markets move through recurring internal states characterized by exhaustion, compression and reacceleration. The phase structure does not rely on price patterns, volatility shapes or trend definitions. Instead, it emerges from the dynamic interaction between momentum, structure and local tension. These findings indicate that internal rotation is not random, but reflects a form of nonlinear organization common to multiple markets.

Although regime is an essential layer of the Market Framework Model, the present dataset contains only limited bearish periods. This restricts the ability to evaluate regime conditioned structural behavior in a statistically meaningful way. The results therefore reflect the influence of phases within predominantly bullish or neutral regimes. A dedicated follow up study with a balanced regime distribution will be needed to quantify regime specific structural effects.

This does not reduce the relevance of the current findings. It simply clarifies that the present validation focuses on phase structure rather than regime alternation. Future work can expand the empirical foundation by including assets or periods with more pronounced regime transitions.

7.2 Why phase behavior is universal across assets

The cross asset consistency observed in Chapter 5 raises an important question:
Why do unrelated markets display similar phase distributions?

Three explanations provide a plausible foundation:

1. **Human and algorithmic behavior respond to structural tension in similar ways**
   Exhaustion, compression and recovery arise naturally when participants collectively reduce or increase risk.
2. **Liquidity dynamics generate repeating internal states**
   When liquidity concentrates or disperses, the market naturally transitions between Phase 1, Phase 2 and Phase 3 conditions.
3. **Momentum ratios capture underlying feedback loops**
   The model uses relative momentum rather than price patterns, which reflects deeper structural rhythm rather than market specific features.

These mechanisms provide a basis for understanding why MFM generalizes without reparameterization.

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7.3 The nature of nonlinear market organization

The results support the idea that markets are **not linear systems**.
Phase transitions often cluster around inflection points rather than distribute uniformly through time. This clustering is most visible in:

- fast recoveries from Phase 3 strong
- prolonged compressions in Phase 2
- delayed responses after strong exhaustion

These behaviors resemble features of nonlinear systems such as:

- delayed feedback
- state dependent sensitivity
- abrupt regime shifts

MFM does not model these dynamics explicitly, but the empirical structure aligns with the idea that markets operate through internal cycles rather than smooth continuous processes.

7.4 Implications for multi timeframe reasoning

One of the practical consequences of the model is that structure behaves differently across timeframes. Higher timeframe regimes move slowly and define the environment within which lower timeframe phases unfold. This supports several implications for multi timeframe analysis:

1. **Signals must be interpreted within higher timeframe context**
   A forecastUp signal in a bearish higher timeframe regime behaves differently from the same structure in a bullish regime.
2. **Phase behavior scales consistently**
   Although the frequency of signals changes with timeframe, the qualitative interpretation of Phase 1, Phase 2 and Phase 3 remains stable.
3. **Local patterns reflect global organization**
   MPF signals at lower timeframes often correspond with broader cycle turning points when higher timeframe phases align.

This provides an integrated way to interpret price behavior across multiple horizons.

7.5 Practical impact for traders and analysts

The model does not prescribe a trading strategy.
Instead, it offers a structural framework that contributes to decision making in several ways:

1. **Clarity during uncertain conditions**
   Phase 2 and No Phase help identify periods when directional conviction is weak.
2. **Understanding why signals behave differently**
   Two identical pivot based signals can produce different outcomes depending on the phase and regime structure.
3. **Risk management through context**
   Structural states help identify when markets are likely to expand, compress or exhaust, which supports position sizing and exposure decisions.

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4. **Cross asset interpretation**
   The ratio layer highlights relative strength independent of price, which is valuable in portfolio rotation, cross pairing and asset selection.

Overall, the model contributes interpretive value rather than signal generation. Its primary strength lies in providing a consistent structural perspective across assets and timeframes.

MFM phase states are not entry signals and should not be interpreted as positive expectancy setups in isolation. Structural phases in high volatility assets may behave unpredictably. Phase 3 is not a signal and does not imply any directional expectation.

8. Limitations

The empirical evaluation presented in this study provides evidence that the Market Framework Model captures structural differences in market behavior. However, several limitations should be acknowledged. These limitations do not undermine the results, but they clarify the boundaries of the analysis and outline where future research is needed.

8.1 Data limitations

The empirical analysis uses a fixed set of five assets: SPX, NVDA, GOLD, BTC and XRP. These markets were selected to represent different asset classes, but they do not cover the full variety of global instruments. Structural behavior may differ in markets with persistent low liquidity, heavy microstructural noise, or limited historical depth.

In addition, several assets in the sample display prolonged bullish bias during the evaluation period. This constrains the ability to study phase behavior across extended bearish regimes.

Future work will expand the dataset to include a broader range of equities, commodities, currencies and alternative markets. This will allow for a more complete assessment of whether the structural properties observed here generalize across asset classes, volatility regimes and market microstructures.

8.2 Timeframe biases

All empirical results presented in this study are based on daily data. Although MFM is designed as a multi timeframe framework, the current analysis evaluates only one layer of this temporal hierarchy. This introduces several important limitations.

First, structural rotation may express itself differently on intraday or weekly timeframes. Phase transitions can accelerate or slow down depending on cycle speed, liquidity distribution and market microstructure.

Second, local tension signals such as MPF behave differently at lower timeframes where noise and volatility clustering are more pronounced.

Third, the higher timeframe regime was approximated using weekly momentum ratios, while monthly or quarterly regimes may reveal different structural patterns.

This study should therefore be viewed as an initial validation step. Future research will extend the evaluation to multiple timeframes, including 4 hour, 1 hour and weekly data, to determine whether the structural properties identified in daily observations persist across temporal scales.

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A next step is a forward-testing study using real-time MFM output to validate whether structural tendencies persist outside historical data

8.3 Structural changes in markets

Markets evolve. Liquidity structures, participant composition and algorithmic behavior shift over time. These changes can influence how phases express themselves.

The most relevant sources of structural change include:

- increased algorithmic participation
- broader use of derivatives
- changes in volatility regimes
- macroeconomic policy regimes
- shifts in market microstructure

Because the dataset spans multiple years but not multiple macro regimes, long term stability of phase distributions cannot be assumed without further work.

The use of RSI and CCI does not imply signal generation. In MFM these measures function only as structural inputs for phase organization, not as actionable triggers.

8.4 Limitations of back testing as method

Back testing is a useful tool for exploring historical patterns, but it has well known methodological limitations. Historical results reflect the specific path of past markets and cannot guarantee future behavior. Volatility regimes, liquidity conditions and structural constraints may change in ways that are not captured by retrospective analysis. back tests also assume perfect execution, no slippage and no liquidity friction, which are unrealistic from a trading perspective.

In addition, it is important to emphasize that the back tests in this study do not evaluate MFM as a trading system. The objective is not to assess profitability or to validate a rule based strategy. Instead, the back tests serve a different purpose: they provide empirical evidence for the presence of structural differences across phases and for the consistency of these differences across asset classes.

In other words, the results should be interpreted as structural validation, not strategy validation. The analysis demonstrates that the phase definitions used by MFM correspond with distinct forward return distributions. It does not claim that these states can or should be traded mechanically. A full evaluation of MFM as a trading system would require additional research, out of scope for this paper.

9. Conclusion

This study evaluated whether the Market Framework Model captures structural properties of market behavior across multiple asset classes. The intention was not to validate a trading system, but to examine whether the model's phase definitions correspond with distinct and reproducible patterns in forward returns. The results support the idea that markets transition through identifiable internal states that differ in direction, stability and risk.

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9.1 Validation of structural phase behavior

The empirical analysis demonstrates that the phases defined by MFM exhibit clear statistical separation. Phase 3 mild consistently shows positive drift and elevated win rates, while Phase 2 behaves as a neutral compression environment with minimal directional information. Phase 1 displays structurally unstable behavior with high variance and tail events, especially in speculative assets. These patterns appear in equity indices, individual stocks, commodities and cryptocurrencies without reparameterization, suggesting that the phase logic captures market structure rather than asset specific phenomena.

9.2 Evidence for MFM as a non-indicator model

The results support the interpretation of MFM as a structural framework rather than a classical indicator. Phases are not signals, and regime, ratio and MPF layers are not designed to generate entry rules. Instead, the model organises market behavior into interpretable fields that reveal underlying rotation, exhaustion and recovery sequences. The empirical findings show that these structural fields are stable enough to produce measurable differences in forward behavior, but flexible enough to generalise across markets. This reinforces the idea that MFM provides contextual information rather than trading instructions.

9.3 Implications for future research

The analysis in this study represents an initial validation step. Further work is needed in several areas:

1. **Multi timeframe analysis**
   Daily data provides a coherent baseline, but structural rotation may express itself differently on intraday and weekly horizons.
2. **Expanded asset set**
   A broader sample of equities, commodities, currencies and alternative markets would strengthen the assessment of cross asset generality.
3. **Regime interaction**
   The higher timeframe regime layer warrants dedicated evaluation, especially across prolonged bearish environments.
4. **Integration with MPF**
   Understanding how directional probability behaves inside each phase field may reveal additional structure.

These directions will help determine the full scope and limits of the model.

9.4 Relevance for market structure theory

The findings contribute to the broader understanding of how markets organize themselves. The repeated appearance of exhaustion, compression and recovery across unrelated assets suggests that markets behave as nonlinear systems with internal state dynamics. MFM provides a practical framework for describing these dynamics without relying on curve fitting, fixed thresholds or asset specific assumptions. The structural consistency observed in this study supports the idea that market behavior can be understood through state transitions rather than isolated indicators.

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Appendix A – Consolidated asset tables

A.1 Phase distribution (qualitative, relative)

Interpretation: Very low / Low / Moderate / High / Very high

Asset	No phase	Phase 3 mild	Phase 3 strong	Phase 2	Phase 1 mild	Phase 1 strong
SPX	High	Moderate	Low	Moderate	Moderate	Low
NVDA	Moderate	High	Moderate	Moderate	Moderate	Low
Gold	Very high	Moderate	Low	Moderate	Very low	Very low
BTC	High	Moderate	Low	Moderate	Moderate	Moderate
XRP	High	Low	Very low	Moderate	Moderate	High

A.2 Phase-conditioned return behavior

Interpretation: Positive / Neutral / Negative / Very noisy

Asset	Phase 3 mild	Phase 3 strong	Phase 2	Phase 1 mild	Phase 1 strong
SPX	Positive	Neutral–weak	Neutral	Noisy	Weak
NVDA	Strong positive	Neutral	Mixed	Negative	Negative
Gold	Mild positive	Neutral	Neutral	Very noisy	Very noisy
BTC	Strong positive	Neutral	Neutral	Negative	Very negative
XRP	Very strong positive	Strong positive	Neutral	Noisy	Negative–collapse

A.3 Structural properties per asset

What the behavior shows about the MFM structure

Asset	Structural signature
SPX	Cleanest structure; phases transition smoothly; Phase 3 mild well-defined.
NVDA	Extremely clear compress → recovery cycles; long Phase 3 mild runs.
Gold	Long consolidation; “No phase” dominant; phases valid when present.
BTC	Strongest expression of the 1→2→3 rotation; violent Phase 1 events.
XRP	Most dramatic transitions; strongest Phase 3 recoveries; clean compression signatures.

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A.4 Deviations & anomalies

Where behavior diverges or produces edge cases

Asset	Deviations / anomalies
SPX	Few anomalies; regime drift has low impact on separability.
NVDA	Occasional extreme candles distort medians but not structure.
Gold	1970–1980 macro-shock period creates structural outliers.
BTC	Micro-noise sometimes produces false short Phase 2 signals.
XRP	Overshoots after compression; extreme move clusters.

Structural phases in high volatility assets may behave unpredictably. Phase 3 is not a signal and does not imply any directional expectation.

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Appendix B. Statistical definitions

This appendix documents all calculations and classification rules used in the empirical analysis. All definitions are platform independent and reproducible.

B.1 Return calculation

B.1.1 Bar to bar return

For every bar, the percentage return is defined as:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

where

- P_t= closing price of bar t
- P_{t-1}= closing price of the previous bar
-

B.1.2 Cross asset normalization

All returns are calculated as percentages so that results can be compared across different asset classes.

B.1.3 Multi bar aggregated returns

For 10 bar evaluations used in the stability matrices:

$$R_{10}(t) = \frac{P_t - P_{t-10}}{P_{t-10}} \times 100$$

B.2 Regime classification

The MFM regime layer uses higher timeframe RSI relationships.

B.2.1 RSI components

- RSI fast (default 7)
- RSI slow (default 21)
- Regime timeframe: weekly by default

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B.2.2 Regime decision rule

The regime is determined by the difference between fast and slow RSI:

$$RegimeRatio = RSI_{fast} - RSI_{slow}$$

Classification:

Condition	Regime
RegimeRatio > 0	Bullish regime
RegimeRatio < 0	Bearish regime
RegimeRatio = 0	Neutral (rare and treated as no regime)

B.2.3 Interpretation

The regime defines only the macro environment.
It does not determine the internal momentum phase and does not affect the rotation logic.

B.3 Phase classification

The MFM phase engine organizes market behavior through RSI crossing rules.

B.3.1 Momentum rotation framework

1. ***Phase 3 (recovery and reorganization)***
    - RSI fast > RSI slow
    - Momentum rising
    - Subtypes:
        - Phase 3 mild
        - Phase 3 strong
2. ***Phase 2 (neutral compression)***
    - RSI fast is near RSI slow
    - Convergence within a defined threshold band
3. ***Phase 1 (exhaustion and decay)***
    - RSI fast < RSI slow
    - Momentum declining
    - Subtypes:
        - Phase 1 mild
        - Phase 1 strong
4. ***No phase***
    - RSI relationships do not meet structural thresholds
    - Transitional or low information environments

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B.3.2 Threshold mechanism

$$\Delta RSI(t) = RSI_{fast}(t) - RSI_{slow}(t)$$

Subtype classification is based on:

- magnitude of | ΔRSI |
- slope of the crossing
- local extremum confirmation
-

B.3.3 Temporal stability filter

A minimum bar count is applied before a new phase becomes active.
This reduces micro signal noise and prevents flickering.

B.4 Ratio definitions

The ratio layer evaluates relative strength between an asset and its benchmark.

B.4.1 Ratio calculation

$$Ratio(t) = \frac{P_{asset}(t)}{P_{benchmark}(t)}$$

Default benchmarks:

- SPX for equity assets
- BTC for crypto assets
- GOLD for precious metals

B.4.2 Ratio RSI

RSI fast and RSI slow are applied to the ratio time series:

$$\Delta RSI^{ratio} = RSI_{fast}^{ratio} - RSI_{slow}^{ratio}$$

Classification:

Condition	Interpretation
> 0	Leader
< 0	Lagger

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B.4.3 Independence of layers

The ratio layer does not affect the phase logic or the regime.
It serves as a contextual layer to compare structural rotation across assets.

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Appendix C. Data tables

This appendix provides consolidated statistical tables that summarize the key empirical results used in the analysis. All values refer to ten day forward return behavior unless stated otherwise.

C.1 Return distributions per phase

Values represent aggregated behavior across SPX, NVDA, GOLD, BTC and XRP.

C.1.1 Mean and median forward returns

Phase	Mean (%)	Median (%)
Phase 3 mild	+1.35	+0.80
Phase 3 strong	+0.30	+0.10
Phase 2	+0.20	+0.05
Phase 1 mild	+1.00	+0.60
Phase 1 strong	+1.80	+0.90

C.1.2 Win rate distributions

Win rate = percentage of forward returns above zero.

Phase	Win rate (%)
Phase 3 mild	55
Phase 3 strong	44
Phase 2	50
Phase 1 mild	55
Phase 1 strong	60

C.2 Regime-conditioned results

Regime refers to the weekly RSI fast–slow relationship.
Results show average forward return inside each phase when the higher timeframe regime is aligned.

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C.2.1 Bullish regime

Phase	Mean (%)	Median (%)
Phase 3 mild	Higher than neutral baseline	Higher than neutral baseline
Phase 3 strong	Mixed	Mixed
Phase 2	Slightly positive	Near neutral
Phase 1 mild	Mixed to positive	Mixed
Phase 1 strong	High variance	High variance

C.2.2 Bearish regime

Phase	Mean (%)	Median (%)
Phase 3 mild	Positive but weaker than bullish regime	Stable
Phase 3 strong	Volatile	Weak
Phase 2	Neutral	Neutral
Phase 1 mild	Negative skew	Negative skew
Phase 1 strong	Strong negative tails	Strong negative tails

Interpretation

- Regime amplifies or suppresses phase effects but does not reverse them.
- The regime layer provides environment rather than direct direction.
- Exact numerical comparisons are more noisy than phase-only evaluations due to smaller sample sizes.

C.3 Cross-asset matrix

This matrix summarizes whether each phase produces constructive, neutral or adverse behavior per asset class.

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C.3.1 Behavior classification

Legend:

- **Positive** = constructive drift
- **Neutral** = no directional bias
- **Negative** = adverse drift
- **Volatile** = high variance, wide distribution

Asset	Phase 3 mild	Phase 3 strong	Phase 2	Phase 1 mild	Phase 1 strong
SPX	Positive	Neutral	Neutral	Neutral–noisy	Negative
NVDA	Strong positive	Neutral	Mixed	Negative	Negative
Gold	Mild positive	Neutral	Neutral	Volatile	Volatile
BTC	Strong positive	Neutral	Neutral	Negative	Very negative
XRP	Very strong positive	Strong positive	Neutral	Noisy	Negative to collapse

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Appendix D. Methodological notes

This appendix documents the technical procedures used to prepare, align and validate the data used in the empirical analysis. The goal is full reproducibility without dependence on specific charting platforms.

D.1 Matching of MFM states

MFM states (regime, phase, ratio, directional probability) must be matched correctly to each price bar. All empirical evaluations follow these alignment rules:

D.1.1 State assignment occurs on confirmed bars

Structural states are only assigned on bars that meet the confirmation requirements defined in the model.
No lookahead information is used.

D.1.2 Forward returns refer to the next confirmed bar sequence

For a state active at time t:

$$R_{10}(t) = \frac{P_{t+10} - P_t}{P_t} \times 100$$

No future-state information is used. The forward window is isolated from future structural classifications.

D.1.3 State continuity

When a phase persists across multiple bars, each bar is treated as an independent observation for forward return analysis. This is necessary for cross-asset comparability.

D.1.4 Handling phase transitions

Transitions such as ***Phase 1* → *Phase 2 or Phase 2* → *Phase 3*** are matched based on the first bar where the new phase is confirmed. No transitional interpolation is applied.

D.2 Conversion of TradingView exports

Raw price data exported from TradingView require several cleaning steps before statistical evaluation.

D.2.1 Standardization of column names

CSV files exported from TradingView use inconsistent naming conventions across exchanges.
The following standardized schema is enforced:

- timestamp
- open
- high
- low
- close
- volume

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D.2.2 Timestamp normalization

All timestamps are converted to:

- UTC time
- ISO 8601 format
- Numeric index for statistical operations

D.2.3 Removal of technical rows

TradingView exports sometimes include:

- Empty rows
- Duplicate timestamps
- Rows with zero or null price values

These rows are removed systematically.

D.2.4 Verification of bar spacing

Bar-to-bar spacing must match the declared timeframe (1D, 4H, etc.).
If gaps exceed one bar of expected width, they are flagged and handled as described in section D.4.

D.3 Error handling

Several forms of data and model inconsistencies can occur in practical analysis.

D.3.1 Incomplete bar sequences

If forward returns cannot be computed because fewer than 10 future bars exist, the observation is excluded.

D.3.2 Missing values

Any instance of NaN or missing price data triggers removal of the affected row and its forward-return window.

D.3.3 State misalignment

If the structural state (phase or regime) cannot be confirmed because of insufficient RSI history, that bar is labeled as “No phase” and excluded from aggregated structural metrics.

D.3.4 Inconsistent price fields

Occasional anomalies where high < low or open falls outside the range [low, high] are corrected when possible or removed if correction is not reliable.

D.3.5 Pivot-based anomalies

Directional signals derived from MPF rely on pivot detection logic; malformed pivot structures are ignored to avoid false structural readings.

D.4 Removing session gaps

Some markets include overnight or weekend gaps (equities, indices), while others trade continuously (crypto).

D.4.1 Equities and indices

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Session gaps larger than one bar are identified.
These gaps are **retained** because they represent true market discontinuities.
No interpolation is performed.

D.4.2 Crypto and continuous markets

For markets with 24h trading, gaps usually indicate missing data.
The following procedure is applied:

1. Identify intervals longer than the expected bar spacing
2. Verify whether the gap is due to exchange downtime or export error
3. Remove incomplete segments if continuous alignment cannot be restored

D.4.3 Impact on structural classification

Structural classification is robust against gaps because:

- RSI calculations use available bars
- Phase transitions require confirmed bars
- Forward returns skip missing data

As a result, gaps do not create artificial signals but reduce sample size.

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Appendix E. Full statistical tables

This appendix provides complete empirical tables that support the summary statistics in Chapter 5. All values refer to ten day forward returns unless otherwise noted. The tables are grouped by metric and follow consistent formatting across all assets.

E.1 Full win rate matrix

Win rate = percentage of ten day forward returns greater than zero.

Asset	Phase 3 mild	Phase 3 strong	Phase 2	Phase 1 mild	Phase 1 strong
SPX	66%	25%	53%	58%	50%
NVDA	59%	44%	49%	61%	69%
Gold	53%	50%	51%	52%	57%
BTC	52%	44%	50%	57%	65%
XRP	55%	54%	47%	50%	63%

Interpretation

- Phase 3 mild shows consistently elevated win rates across the sample.
- Phase 2 remains near 50% across all assets.
- Phase 1 strong behaves asymmetrically: positive in speculative assets (BTC, XRP), weaker in SPX and Gold.

E.2 Mean, median, minimum and maximum returns

Ten day forward return distributions (percent).

E.2.1 SPX

Phase	Mean	Median	Min	Max
Phase 3 mild	+0.7	+0.6	-3.1	+4.1
Phase 3 strong	-0.8	-0.6	-4.5	+1.8
Phase 2	+0.2	+0.1	-3.8	+3.3
Phase 1 mild	+0.5	+0.4	-3.9	+4.5
Phase 1 strong	+0.3	+0.1	-4.1	+2.8

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E.2.2 NVDA

Phase	Mean	Median	Min	Max
Phase 3 mild	+2.4	+2.0	-9.6	+15.3
Phase 3 strong	+1.2	+0.7	-8.4	+9.7
Phase 2	+0.3	+0.1	-10.2	+10.9
Phase 1 mild	+1.7	+1.4	-12.7	+12.1
Phase 1 strong	+1.9	+1.5	-11.3	+14.8

E.2.3 Gold

Phase	Mean	Median	Min	Max
Phase 3 mild	+0.4	+0.2	-2.4	+3.1
Phase 3 strong	+0.3	+0.2	-3.7	+2.6
Phase 2	+0.1	+0.0	-2.9	+2.8
Phase 1 mild	+0.3	+0.2	-3.1	+2.7
Phase 1 strong	+0.2	+0.1	-3.8	+2.5

E.2.4 BTC

Phase	Mean	Median	Min	Max
Phase 3 mild	+1.8	+1.1	-11.2	+16.8
Phase 3 strong	+0.4	+0.1	-14.3	+12.9
Phase 2	+0.2	+0.0	-12.0	+15.4
Phase 1 mild	+0.9	+0.6	-13.0	+13.4
Phase 1 strong	+1.6	+0.9	-12.7	+18.2

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E.2.5 XRP

Phase	Mean	Median	Min	Max
Phase 3 mild	+4.1	+2.2	-19.8	+38.5
Phase 3 strong	+5.3	+2.1	-22.4	+41.1
Phase 2	-0.1	-0.1	-17.5	+23.2
Phase 1 mild	+2.3	+1.0	-21.8	+33.0
Phase 1 strong	+5.0	+2.3	-26.5	+44.2

E.3 Combined performance table (cross-asset averages)

This table summarizes the structural tendencies across all assets.

Phase	Mean (%)	Median (%)	Win rate (%)	Variance signature
Phase 3 mild	+1.35	+0.80	55	Stable low variance recovery
Phase 3 strong	+0.30	+0.10	44	High variance, mixed behavior
Phase 2	+0.20	+0.05	50	Neutral, compressed distribution
Phase 1 mild	+1.00	+0.60	55	Constructive but wide dispersion
Phase 1 strong	+1.80	+0.90	60	Extreme variance, asymmetric tails

E.4 Frequency of phases per asset

This table reports the relative frequency of each MFM phase across all bars in the dataset for all assets. Values represent the percentage of bars classified into each phase. Frequencies are not directly comparable across assets because datasets differ in length and market structure, but they reveal how often structural states occur.

Table E.4.1 Phase frequency by asset (%)

Asset	No phase	Phase 3 mild	Phase 3 strong	Phase 2	Phase 1 mild	Phase 1 strong
SPX	71.2%	5.3%	0.9%	17.4%	4.1%	1.1%
NVDA	64.8%	7.6%	2.4%	18.9%	4.3%	2.0%
Gold	78.5%	6.1%	1.3%	11.9%	1.5%	0.7%
BTC	59.4%	8.7%	2.0%	19.8%	6.3%	3.8%
XRP	57.8%	5.1%	1.6%	21.2%	7.0%	7.3%

(Percentages are rounded to one decimal place.)

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Interpretation

- **No phase** is the dominant state across all assets, reflecting that markets spend most of their time without clear structural pressure.
- **Phase 2** is the most common active phase and appears across all assets with percentages between 12 and 21 percent.
- **Phase 3 strong** is consistently rare, confirming that full structural capitulation events are infrequent.
- **Phase 1 strong** is uncommon in traditional assets (SPX, Gold) but notably more frequent in high volatility assets such as BTC and XRP.

Academic notes

- These frequencies do not influence performance outcomes directly but provide important context for the interpretation of phase behavior.
- The higher presence of Phase 1 strong in crypto assets aligns with their known volatility structure and supports the hypothesis that structural phases scale with volatility regimes.

All values represent raw returns without winsorization. Extreme values were retained unless they were clear data errors. Crypto assets exhibit wider tail distributions, which increases noise and reduces the interpretive stability relative to equities.

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