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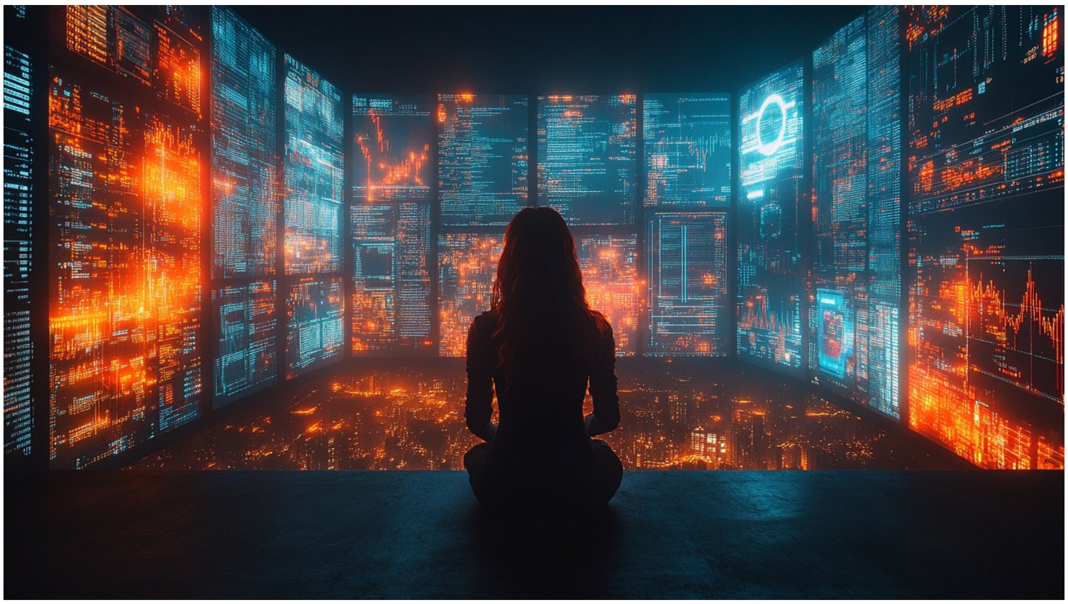

Signal vs. Noise

How AI Is Transforming Macroeconomic Analysis

— and Where It Fails

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1 Introduction: The Analytical Revolution

The intersection of artificial intelligence and macroeconomic analysis represents one of the most consequential shifts in financial markets since the advent of electronic trading. Yet most discussions of AI in finance oscillate between two unhelpful extremes: breathless enthusiasm about machines replacing human analysts, or dismissive skepticism that treats every AI tool as a marketing gimmick.

The truth, as observed from several years inside one of the most sophisticated on-chain analytics platforms in the world, is more nuanced and more interesting than either extreme.

DINNER TABLE VERSION

Imagine you hired the world's fastest research assistant. This assistant can read every financial report, every Federal Reserve speech, every blockchain transaction ever recorded — and summarize them for you before your morning coffee gets cold. That assistant is AI.

Now imagine that same assistant has no idea what any of it *means*. It cannot tell you whether a wallet moving $50 million in Bitcoin at 3 AM is a hedge fund rebalancing, an exchange doing routine maintenance, or a government seizing assets. It just tells you the money moved.

The question is not whether AI is useful. It is spectacularly useful. The question is whether you are skilled enough to use it without being misled by it. That question separates the analysts who will thrive in the next decade from those who will be replaced — not by AI, but by other humans who use AI better than they do.

This paper examines the specific capabilities and failure modes of AI in macroeconomic analysis, drawn from direct experience building and operating analytical systems at institutional scale. It is organized around a central thesis: **AI has fundamentally changed the economics of information access while leaving the economics of information interpretation largely unchanged.** The analysts who understand this distinction will dominate the next era of financial markets.

2 The AI Toolkit for Macro Analysis

The term "AI" encompasses a broad range of technologies with very different capabilities. For macroeconomic analysis, three categories matter.

2.1 Large Language Models (LLMs)

Large language models — GPT-4, Claude, Gemini, and their successors — are information compression engines. Their primary value in macro analysis is not generation but *synthesis*: the ability to read, summarize, and cross-reference vast quantities of text in seconds.

Table 1: LLM Capabilities in Macro Analysis

Task	LLM Performance	Human Advantage
Fed speech analysis	Excellent: identifies hawkish/dovish shifts across 50+ speeches in minutes	Contextual reading: understands what the Fed *cannot* say publicly
BIS/IMF report summarization	Excellent: extracts actionable passages from 100-page documents	Knows which passages matter for specific trading theses
Cross-asset narrative construction	Poor to fair: generates plausible-sounding narratives that may be internally inconsistent	Essential: narrative coherence requires domain expertise
Earnings call analysis	Good: identifies tone shifts, keyword frequency changes	Understands industry dynamics that give context to tone shifts
Geopolitical risk assessment	Poor: lacks real-time information; training data introduces lag	Critical: connects intelligence signals to market implications

The key insight is that LLMs are most valuable at the beginning and end of the analytical process — initial information gathering and final report drafting — but least valuable in the middle, where judgment, synthesis, and thesis construction occur.

2.2 Machine Learning Classifiers

Machine learning classifiers are the workhorses of on-chain analytics. These systems assign labels to blockchain addresses based on observed behavioral patterns: exchange wallets, DeFi protocols, institutional accumulators, miners, smart money, and hundreds of sub-categories.

The classification pipeline at scale operates in several stages:

1. **Known entity seeding:** Start with addresses whose owners are publicly known (exchange hot wallets, protocol treasuries, known funds).
2. **Behavioral clustering:** Group unknown addresses by transaction patterns (frequency, size, counterparties, timing).
3. **Feature engineering:** Extract 50–200 features per address: transaction velocity, average hold time, counterparty diversity, gas price sensitivity, interaction with known DeFi protocols, and others.
4. **Classification:** Apply supervised and semi-supervised models to assign labels. Common architectures include random forests, gradient-boosted trees, and graph neural networks.
5. **Confidence scoring:** Assign a confidence metric to each label. This is the hardest and most important step.
6. **Temporal validation:** Continuously re-evaluate labels as new transactions occur. A wallet labeled “long-term holder” that suddenly begins distributing must be re-classified.

CRITICAL FAILURE MODE: CONFIDENCE CALIBRATION

The single most dangerous failure in on-chain analytics is the presentation of low-confidence labels as if they were high-confidence facts. When a dashboard shows "Smart Money: Accumulating BTC" — is that label 95% confident or 55% confident? Most platforms do not tell you. The analyst who does not ask this question is building their thesis on sand.

During my time working with wallet labeling pipelines, we found that approximately 30–40% of labels at any given time had confidence scores below 70%. These labels were directionally useful in aggregate but potentially misleading for individual wallets. The industry standard practice of displaying labels without confidence intervals is, in my assessment, the single largest source of analytical error in on-chain research.

2.3 Quantitative Signal Processing

The third category encompasses traditional quantitative methods enhanced by modern computing power: time-series analysis, correlation matrices, regime-detection algorithms, and anomaly detection systems. These are not "AI" in the popular sense, but they benefit enormously from the same infrastructure improvements (GPU computing, cloud scaling, low-latency data feeds) that power LLMs and classifiers.

Key quantitative signals in crypto-macro analysis include:

- **Stablecoin mint/burn ratios:** Net minting of USDC and USDT correlates with capital inflows to crypto. A sustained mint/burn ratio above 1.0 historically precedes risk-on environments.
- **Futures funding rates:** Positive funding rates indicate leveraged long positioning; negative rates indicate short positioning. Extreme readings in either direction precede liquidation cascades.
- **On-chain velocity:** The rate at which tokens change hands. Declining velocity in a rising-price environment signals accumulation; rising velocity signals distribution.
- **Exchange netflow:** Net movement of assets to or from exchange wallets. Sustained outflows suggest accumulation for cold storage; sustained inflows suggest preparation to sell.
- **Treasury yield curve shape:** The 2Y/10Y spread and the 3M/10Y spread remain the most reliable recession indicators in traditional macro. Their predictive power in crypto is mediated through institutional allocation decisions.

3 Where AI Excels: The Information Compression Revolution

Signal emerging from noise: the core challenge of AI-augmented macro analysis.

3.1 Volume Processing

The most immediate and unambiguous benefit of AI in macro analysis is raw throughput. Consider the daily information load facing an institutional macro analyst:

Table 2: Daily Information Volume for an Institutional Macro Analyst

Source	Daily Volume	Human Processing	AI Processing
Fed/ECB/BOJ communications	5–15 documents	3–6 hours	2–5 minutes
Sell-side research notes	20–50 notes	2–4 hours	5–10 minutes
Earnings transcripts	5–20 calls/day	1–3 hours each	1–2 min each
On-chain data alerts	100–500 alerts	Impossible to review all	Real-time filtering
News/social media	Thousands of items	Selective sampling	Comprehensive scan
Regulatory filings	Variable	Hours per document	Minutes per document

No human can process this volume. Before AI, the solution was team-based coverage: one analyst covers rates, another covers credit, another covers equities, another covers crypto. AI does not eliminate specialization, but it allows each specialist to maintain peripheral awareness of adjacent domains at a level that was previously impossible.

3.2 Cross-Domain Correlation Discovery

AI systems excel at identifying statistical relationships across datasets that human analysts rarely cross-reference. Some examples from practice:

1. **Stablecoin supply growth and Treasury demand:** Machine learning models identified that periods of rapid stablecoin minting correlated with increased demand for short-duration Treasury bills — a relationship that became obvious in retrospect (stablecoin reserves must be parked somewhere) but was not widely discussed until quantitative systems surfaced it.
2. **Ethereum gas prices and DeFi yield compression:** High gas prices reduce the profitability of DeFi yield strategies for smaller participants, concentrating activity among larger wallets. This creates measurable shifts in wallet size distributions that precede changes in protocol TVL by 2–5 days.
3. **Bitcoin hashrate migrations and energy market signals:** Geographic shifts in mining hashrate (detectable through pool distribution analysis and IP geolocation of node traffic) correlate with regional energy price changes and regulatory actions, often providing 1–3 weeks of lead time.

KEY INSIGHT

The value of cross-domain correlation discovery is not in the correlations themselves — many are spurious — but in the *hypotheses* they generate for human analysts to investigate. The machine says "these two things moved together 73% of the time over the last 18 months." The human analyst determines whether that relationship is causal, coincidental, or driven by a common third factor.

3.3 Speed of Initial Synthesis

A concrete example illustrates this capability. In December 2024, the Federal Reserve released its Summary of Economic Projections alongside the FOMC decision. Within 90 seconds of publication, an LLM-powered system could:

1. Compare the new dot plot against the September projection, identifying which participants shifted their rate expectations.
2. Extract the changes to GDP, unemployment, and PCE forecasts versus prior projections.
3. Cross-reference Powell's prepared statement against the previous statement, highlighting every changed word and phrase.
4. Generate a preliminary "hawkish/dovish scorecard" based on the aggregate changes.

A human analyst performing the same tasks would need 30–60 minutes. The LLM does not understand monetary policy better than the human. But it compresses the mechanical comparison work to near-zero, freeing the human to spend those 30–60 minutes on what matters: interpreting what the changes mean.

4 Where AI Fails: The Interpretation Gap

4.1 Confidence Calibration

This failure mode deserves extended treatment because it is the most consequential and least discussed.

AI systems — particularly LLMs — present all outputs with uniform linguistic confidence. There is no tonal difference between a high-confidence factual statement and a speculative inference. Consider two LLM outputs:

> *"Bitcoin's 30-day moving average crossed above the 200-day moving average on January 15th."*
> *"The current accumulation pattern suggests institutional positioning ahead of a major regulatory announcement."*

The first statement is verifiable and almost certainly correct. The second is speculative interpretation dressed in the language of certainty. Yet both are delivered with identical confidence by most LLM systems.

DINNER TABLE VERSION

Imagine your research assistant tells you two things: "The sky is blue" and "The CEO is about to resign." Both statements are delivered in the same calm, confident voice. One is observable fact. The other is inference based on fragmentary signals. If you cannot tell which is which, your assistant is not helping you — it is setting a trap for you.

This is exactly what happens when AI systems present analysis without confidence scores. Every output sounds equally certain. The analyst who does not independently verify the confidence level of every AI-generated conclusion will eventually make a catastrophic decision based on a low-confidence output that sounded authoritative.

In the wallet labeling context, confidence calibration manifests as the difference between:

- A wallet labeled "Binance Hot Wallet" with 99.9% confidence (based on known deposit address + transaction pattern + on-chain attestation).
- A wallet labeled "Institutional Accumulator" with 62% confidence (based on behavioral clustering that matches institutional patterns but could also match a sophisticated individual or an OTC desk).

Both labels appear identically on most dashboards. The analyst who treats them as equally reliable will misread market positioning.

4.2 Regime Change Detection

Machine learning models are, by construction, backward-looking. They identify patterns in historical data and project those patterns forward. This works well in stable regimes and fails catastrophically at structural breaks.

Table 3: Regime Changes That Broke ML Models

Event	What Models Expected	What Happened
ZIRP to 5%+ rates (2022–23)	Risk asset correlations to hold	Correlation structure reorganized entirely
TerraUST collapse (May 2022)	Algorithmic stablecoins to maintain peg within historical variance	Complete de-peg and $40B loss in days
FTX collapse (Nov 2022)	Exchange counterparty risk to be contained	Systemic contagion across DeFi, CeFi, and mining
Bitcoin ETF approval (Jan 2024)	Continued correlation between BTC price and on-chain metrics	Institutional flows decoupled price from on-chain signals
Stablecoin regulatory shift (2025–26)	Reserve compositions to remain stable	GENIUS Act compliance forcing reserve restructuring

The fundamental problem is that ML models optimize for pattern recognition within a distribution, not for detecting when the distribution itself has changed. Human analysts, with their understanding of institutional behavior, regulatory dynamics, and political incentives, are far better equipped to anticipate regime changes — even if they cannot time them precisely.

4.3 Narrative Construction

Markets are narrative-driven systems. The same data point can support opposing market narratives depending on framing:

- **CPI comes in at 3.2% vs. 3.0% expected:**
  - Bearish narrative: "Inflation is sticky. The Fed will hold rates higher for longer. Risk assets repriced."
  - Bullish narrative: "The year-over-year trend continues to decline from the 9% peak. The disinflation trend is intact. This is a buying opportunity."
- **Bitcoin breaks $100,000:**
  - Bullish narrative: "Institutional adoption validated. ETF inflows accelerating. New asset class."
  - Bearish narrative: "Round number resistance. Retail FOMO indicator. Distribution phase for early holders."

AI systems can generate both narratives. They cannot determine which narrative the market will adopt. That determination requires understanding of positioning, sentiment, liquidity conditions, and the behavioral tendencies of the dominant market participants at that moment in time. This is the domain of experienced human analysts, and it remains the primary source of alpha.

5 The Latency Problem: Data Decay in On-Chain Analytics

The information half-life: every signal decays from the moment it is generated.

5.1 The Information Half-Life

Every piece of market-relevant information has a half-life: the time after which its value to a trader is reduced by 50%. In on-chain analytics, the information half-life has been compressing relentlessly.

Table 4: Information Half-Life Compression in On-Chain Analytics

Signal Type	2020	2023	2025
Whale wallet movement	Hours	15–30 min	2–5 min
Exchange netflow shift	4–8 hours	1–2 hours	15–30 min
DeFi protocol TVL change	12–24 hours	2–4 hours	30–60 min
Smart money accumulation pattern	Days	Hours	30 min–2 hours
Stablecoin mint/burn	6–12 hours	1–2 hours	10–30 min

This compression is driven by three factors: (1) more participants monitoring the same data sources, (2) faster indexing and labeling pipelines, and (3) automated trading systems that act on on-chain signals without human intervention.

5.2 The Pipeline Latency Stack

Understanding where latency enters the analytical pipeline is critical for assessing the reliability of any signal:

1. **Block confirmation:** 10–15 minutes for Bitcoin, approximately 12 seconds for Ethereum post-Merge. This is the irreducible minimum.
2. **Indexing:** The time for a blockchain indexer (Nansen, Etherscan, Dune) to process and store the transaction. Typically 1–30 seconds after confirmation.
3. **Labeling:** The time for the classification pipeline to assign or update labels on involved addresses. This ranges from real-time (for known addresses) to hours (for addresses requiring behavioral re-clustering).
4. **Aggregation:** The time for the signal to be aggregated into a dashboard metric (e.g., "exchange netflow" requires aggregating thousands of individual transactions). Typically 1–5 minutes.
5. **Alert delivery:** The time for the signal to reach the analyst via dashboard, API, or notification system. Typically 5–60 seconds.
6. **Human interpretation:** The time for the analyst to see, contextualize, and act on the signal. Highly variable: 30 seconds to hours.

Total pipeline latency from on-chain event to human decision: typically 5–30 minutes for well-instrumented systems. By the time a signal reaches a human analyst, automated systems have already acted on it.

THE LATENCY PARADOX

The better your data pipeline gets, the less your edge comes from data access and the more it comes from interpretation quality. When everyone has the same data within minutes, the competitive advantage shifts entirely to: (1) superior contextual understanding, (2) higher-confidence labeling, and (3) faster narrative construction. All three are human capabilities augmented by — but not replaced by — AI.

6 The Practitioner's Framework: Integrating AI into Macro Analysis

After several years operating at the intersection of AI tools and institutional macro analysis, I have distilled the operational principles that separate effective AI-augmented analysis from AI-dependent analysis.

6.1 Principle 1: Use AI for Volume, Not for Judgment

The correct deployment of AI in macro analysis follows a strict division of labor:

THE VOLUME/JUDGMENT DIVIDE

AI handles:

- Reading and summarizing documents (Fed minutes, BIS reports, earnings calls)
- Monitoring on-chain metrics across thousands of wallets simultaneously
- Calculating and updating quantitative indicators in real time
- Screening for anomalies in transaction patterns, price movements, and fund flows
- Drafting initial report structures and data compilations

The human handles:

- Determining which data points matter for the current thesis
- Constructing the narrative that connects disparate data points
- Assessing the confidence level of AI-generated labels and outputs
- Anticipating regime changes based on institutional knowledge
- Making the final call on positioning and risk

The failure mode is allowing AI outputs to substitute for judgment. When an analyst says "the AI flagged this as significant," the question must always be: significant *according to what criteria*, and *how confident is that assessment*?

6.2 Principle 2: Demand Confidence Scores

Any analytical system — AI or human — that produces conclusions without confidence estimates is incomplete. This principle applies universally:

- **Wallet labels:** Every label should carry a confidence score. "Exchange wallet (99%)" is actionable. "Smart money (58%)" is a hypothesis requiring verification.
- **Sentiment analysis:** "Hawkish tone (85% confidence based on keyword density and semantic analysis)" is useful. "Hawkish tone" without qualification is dangerous.
- **LLM summaries:** Request that any LLM-generated summary explicitly flag statements where the model's confidence is low. Modern LLMs can be prompted to do this, though they are imperfect at self-calibration.
- **Correlation signals:** "These two metrics correlated at 0.78 over the last 18 months with a p-value of 0.002" is analytically useful. "These metrics are correlated" is not.

6.3 Principle 3: Maintain Independent Frameworks

The most dangerous outcome of AI adoption in macro analysis is framework dependency: the analyst who can no longer construct a thesis without AI-generated inputs. This creates fragility at exactly the moment when robustness matters most — during regime changes, data outages, or model failures.

THE DEPENDENCY TEST

Ask yourself: *If every AI tool I use went offline for 48 hours, could I still produce a credible* *macro analysis?*

If the answer is no, you have a dependency problem. Your AI tools have replaced your analytical framework rather than augmenting it. The solution is to maintain a "manual mode" capability: a set of core indicators you track independently, a macro thesis you update weekly without AI assistance, and a decision framework that works with or without algorithmic inputs.

Independent frameworks serve as the immune system against AI failure. When the model says one thing and your independent framework says another, the disagreement is itself a valuable signal that demands investigation.

7 The Competitive Landscape: Who Wins in the AI-Augmented Era

7.1 The New Hierarchy of Analytical Advantage

The integration of AI into macro analysis has restructured the competitive hierarchy:

Table 5: The New Analytical Hierarchy

Tier	Characteristic	Competitive Position
Tier 1	Expert humans + well-tuned AI tools + proprietary data	Dominant: the AI amplifies existing expertise
Tier 2	Expert humans without AI tools	Declining: still producing good analysis but slower
Tier 3	Mediocre humans + excellent AI tools	Exposed: the AI makes analytical weaknesses visible faster
Tier 4	AI-only (fully automated)	Fragile: performs well in stable regimes, fails catastrophically at regime changes

The critical observation is that **AI amplifies existing capability rather than creating it**. A strong analyst with AI tools becomes dramatically more productive. A weak analyst with the same tools produces more output but not better analysis — and the increased volume of mediocre analysis may actually be worse than less output, because it creates a false sense of comprehensive coverage.

7.2 Implications for Institutional Research

For institutional research operations (sell-side, buy-side, consulting), the AI transition has specific strategic implications:

1. **Headcount reallocation, not reduction.** The total amount of analytical work has not decreased — it has shifted from information gathering to interpretation. Firms that reduce analyst headcount in response to AI adoption will find themselves with faster data pipelines feeding into fewer brains capable of interpreting the output.
2. **Data infrastructure becomes a moat.** The quality of your data pipeline — latency, label confidence, coverage breadth — is now a primary competitive differentiator. Firms with

proprietary data sources and high-confidence labeling pipelines have structural advantages that AI tools amplify.

3. **Cross-domain expertise becomes more valuable.** When AI handles the volume work within domains, the scarce resource becomes the ability to synthesize across domains: connecting macro indicators to on-chain signals, regulatory developments to market structure, and geopolitical events to capital flows. Analysts with multi-domain expertise (finance + technology + policy, for example) become disproportionately valuable.

8 Case Studies: AI in Practice

8.1 Case Study 1: The Fed Pivot Signal (Late 2023)

In late 2023, market participants debated whether the Federal Reserve would begin cutting rates in 2024. LLM analysis of Fed communications identified a subtle but measurable shift: the ratio of forward-looking dovish phrases to backward-looking inflation warnings increased across multiple Fed governors' speeches over a 6-week period. This shift preceded the explicit "dot plot" pivot by approximately 3 weeks.

What the AI did well: Quantified a linguistic pattern across 40+ speeches that no human analyst could have tracked with the same precision.

What the AI missed: The timing of the actual pivot was driven by political dynamics (election year, labor market data revisions) that linguistic analysis could not capture. The AI identified the direction correctly but could not predict the timing.

Lesson: AI excels at directional pattern recognition. Timing requires human judgment about institutional incentives.

8.2 Case Study 2: On-Chain Accumulation Before the Bitcoin ETF (Late 2023)

In the months preceding the Bitcoin ETF approval in January 2024, on-chain analytics platforms detected sustained accumulation by wallets classified as "institutional." However, the confidence levels on these labels varied significantly:

- Some "institutional" wallets were clearly associated with known ETF applicants (high confidence, 90%+).
- Others were classified as institutional based on transaction size and pattern alone (moderate confidence, 60–75%).
- A meaningful fraction of the "accumulation" was later revealed to be OTC desks pre-positioning inventory for expected ETF-driven demand (a different thesis than direct institutional buying).

What the AI did well: Identified the aggregate accumulation trend with high accuracy.

What the AI missed: The distinction between direct institutional buying and OTC inventory building. Both look similar on-chain but imply different market dynamics.

Lesson: Aggregate signals are reliable; wallet-level attribution requires confidence-weighted analysis.

8.3 Case Study 3: The Stablecoin De-risk Signal (2025)

As the GENIUS Act moved toward passage, stablecoin issuers began restructuring reserves to comply with the new 1:1 backing requirements. This created detectable on-chain and market signals:

- Increased Treasury bill purchases by entities associated with stablecoin reserves.
- Reduced exposure to commercial paper and corporate bonds in reserve attestations.
- Migration of reserve assets to qualified custodians.

AI systems flagged these movements in real time. Human analysts who understood the regulatory context could interpret them as compliance-driven repositioning rather than a risk signal. Analysts relying purely on pattern matching may have interpreted the increased Treasury purchases as a "flight to safety" — a completely different narrative with different trading implications.

Lesson: The same on-chain pattern can support contradictory narratives. Regulatory context, which requires human expertise, determines the correct interpretation.

9 Looking Forward: The Next Three Years

9.1 What Will Improve

1. **Confidence calibration:** This is an active area of research across AI labs. Within 2–3 years, expect LLMs and classifiers to provide meaningful confidence intervals with outputs. This will be the single most impactful improvement for analytical applications.
2. **Multi-modal synthesis:** Current AI tools process text, numbers, and on-chain data in separate pipelines. The next generation will integrate these into unified analytical systems that can simultaneously process a Fed speech, the corresponding market reaction, on-chain flow changes, and social media sentiment — and identify the causal chain connecting them.
3. **Latency reduction:** Indexing and labeling latency will continue to compress, approaching real-time for high-priority signals. This will further shift the competitive advantage from data access to interpretation speed.

9.2 What Will Not Change

1. **The need for human judgment at regime changes.** No amount of historical pattern matching can anticipate truly novel market structures. Human analysts with institutional knowledge will remain essential for navigating structural breaks.
2. **The narrative economy.** Markets will continue to be driven by narratives, and narrative construction will remain a fundamentally human skill. AI will get better at *generating* plausible narratives but not at *selecting* the correct one.
3. **The confidence problem.** Even with improved calibration, AI systems will always have an incentive to present outputs confidently (users prefer confident-sounding tools). The burden will remain on the analyst to demand and evaluate confidence metrics.

10 Conclusion: The Analyst's New Job Description

The macro analyst of 2026 and beyond has a fundamentally different job than the macro analyst of 2019. The old job was 70% information gathering and 30% interpretation. The new job is 10% information gathering (because AI handles the volume) and 90% interpretation, judgment, and narrative construction.

This is not a worse job. It is a better one. The tedious parts have been automated. What remains is the intellectually demanding core: making sense of complex, contradictory information in environments where the rules themselves are changing.

THE PRACTITIONER'S SUMMARY

Three principles:

1. **Use AI for volume, not for judgment.** Let the machine process, filter, and surface. Never let it conclude.
2. **Demand confidence scores, not just outputs.** Any AI system that gives you an answer without telling you how confident it is in that answer is dangerous.
3. **Maintain independent macro frameworks.** If you cannot explain your thesis without referencing an AI output, you do not have a thesis — you have a dependency.

The analysts who thrive in this environment are the ones who treat AI as what it is: the most powerful research assistant ever built, operated by the most powerful pattern-matching engine ever created, that has absolutely no idea what any of it means.

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