Investigating the relationship between the M2 Money Supply and ETH through trading strategies

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Abstract

As the M2 money supply, which includes cash, checking deposits, and near-money assets, increases without a corresponding rise in economic value, the purchasing power of each unit in M2 (USD) diminishes relative to tangible and digital assets like Ethereum (ETH). This devaluation prompts investors to divest from USD into alternative assets, anticipating a correction in USD value. The purpose of this bot is to use M2 alone as a proxy to predict changes in ETH.

1 Context

In response to the slowdown in economic activity caused by the COVID-19 pandemic, the Federal Reserve implemented aggressive monetary policies to inject liquidity into the economy. These measures included lowering interest rates to near zero, quantitative easing through large-scale asset purchases, while in parallel the U.S. Congress granted stimulus checks to the citizenry. As a result, M2 saw an unprecedented increase, with a 24.2% rise from March 2020 to March 2021 alone. This influx of money was intended to stimulate economic activity by boosting consumer spending and investment.

The Federal Reserve believes that increasing M2 can help stabilize the economy during crises by ensuring that there is sufficient liquidity to support economic activities. The Federal Reserve attempts to prevent deflation by making money more available, encouraging borrowing and spending, expecting economic growth to be a downstream effect. This approach is grounded in the belief that a higher money supply can lead to increased demand for goods and services, supporting businesses and employment that otherwise would fail if activity was interrupted by, in this case, social distancing and quarantine.

Despite the Fed's intentions, the increase of M2 faced significant criticism. Critics argued that the increased money supply contributed to inflationary pressures. For example, the recent uptick in M2 has been linked to rising inflation, as seen in the 0.98% increase from February to March 2024, which suggests an imbalance between available funds and the supply of goods and services. Critics have voiced concerns about the long-term implications of this strategy, such as the potential for high inflation to erode purchasing power and create economic instability. Broader criticisms are also levied regarding the stagnation of growth despite the increased money supply, arguing that merely increasing M2 does not address underlying structural issues in the economy, such as productivity and innovation, which are crucial for sustained economic growth.

Given this backdrop, it begs the question to what extent changes in M2 can serve as acute indicators for shifts in consumer sentiment and the second-order change in the value of ETH.

2 Trading Strategies

Fundamentally any trading strategy has to beat a base-case, usually the growth of the S&P500. With respect the ETH and M2, the trading strategy has to beat "buying and holding" Ethereum at the start of the studied time period. Here, we're interested in the period following March 2020 as that's when M2's growth in supply accelerated and the market was more sensitive to this one concern. A portfolio starting at $10,000 USD at this time would mature, at the time of writing, to $167,745.73 USD.

From here, the simplest trading strategy is based on a proportional linear function ("Linear Proportional", "Simple Strategy") to determine the percentage of the portfolio to buy or sell. This strategy assumes a direct proportional relationship between the magnitude of the M2 money supply change and the trading action. Mathematically, the percentage of the portfolio to trade (trade_percentage) was calculated as:

$$\text{trade\_percentage} = \frac{\text{abs}(m2\_change)}{\text{max\_threshold}}$$

where max_threshold is the maximum M2 change threshold set to 2.0%. The strategy aimed to buy or sell up to 100% of the portfolio based on the magnitude of the M2 change, providing a straightforward and easy-to-understand mechanism. This strategy netted $172,569.41 USD, but approach did not account for the potential non-linear relationships between M2 changes and Ethereum price movements.

2.1 Refined Strategy

To improve the strategy, partial buys and sells were introduced based on the magnitude of the M2 percentage change. Three discrete thresholds were defined:

- Small M2 Change: 0.1% to 0.5% (25% of the balance)
- Medium M2 Change: 0.5% to 1.0% (50% of the balance)
- Large M2 Change: Greater than 1.0% (100% of the balance)

This refinement aimed to provide a more granular response to M2 changes, yet it resulted in worse performance with a final portfolio value of approximately $68,127.70.

2.2 Enhanced Strategy

Because discrete values somehow damaged the gains, moving averages were incorporated to smooth out the M2 and ETH percentage changes over a specified window (e.g., 4 weeks). This approach aimed to reduce noise and make the trading decisions more robust, theoretically as news mayu have percolated and consumers had enough time to take action . Additionally, I used more granular thresholds:

- Very Small M2 Change: 0.1% to 0.3% (10% of the balance)
- Small M2 Change: 0.3% to 0.5% (25% of the balance)
- Medium M2 Change: 0.5% to 0.7% (50% of the balance)
- Large M2 Change: 0.7% to 1.0% (75% of the balance)
- Very Large M2 Change: Greater than 1.0% (100% of the balance)

This enhanced strategy further degraded the portfolio performance, with a final value of $60,188.11.

2.3 Dynamic Strategy

The lesson from the previous two algorithms wast that discrete strategies seem to be bad. Therefore, to create a more dynamic strategy, a continuous linear function was used to determine the percentage of USD or ETH to buy or sell based on the magnitude of the M2 change. This function allowed the trade percentage to vary smoothly with the M2 change:

$$\text{trade\_percentage} = \frac{\text{abs}(m2\_change)}{\text{max\_threshold}}$$

This approach resulted in a final portfolio value of $66,715.72 USD, better than the enhanced (most discrete) strategy, but still terrible compared to buying and holding.

2.4 Exponential Function

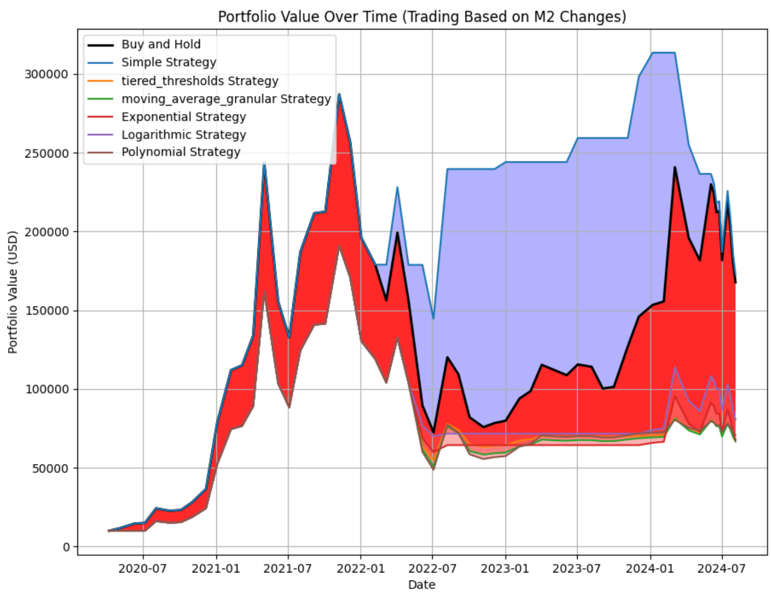

Figure 1: This figure shows the portfolio over time of each trading strategy discussed. The blue highlighted area shows the region where any trading strategy exceeded the portfolio balance of "Buy and Hold", and the red highlighted area shows the region where trading strategies underperform "Buy and Hold.

It was possible that using a function to determine the quantity bought and sold was too simple, and to this end various non-linear functions were explored, starting with an exponential function. The exponential strategy aimed to model the trade percentage using an exponential growth curve:

$$\text{trade\_percentage} = e^{\frac{\text{abs}(m2\_change)}{k}} - 1$$

where k is a scaling factor controlling the curve's steepness. This approach assumed that larger M2 changes would result in disproportionately larger trading actions, reflecting a more aggressive response to significant changes in the money supply. However, this strategy led to a portfolio value of approximately $67,662.11, a limited improvement over the linear approach.

Strategy	Final Balance	vs. B/H
Buy and Hold	$167,745	
Linear Proportional	$172,569	+2.9%
Tiered Thresholds	$68,127	-59.4%
Moving Average	$60,188	-64.1%
Linear	$66,715	-60.2%
Exponential	$67,662	-59.7%
Logarithmic	$80,452	-52.0%
Polynomial	$70,688	-57.9%

Table 1: This table compares the final balances of various trading strategies against the Buy and Hold strategy. The "vs. Buy/Hold" column indicates the percentage change in final balance compared to the Buy and Hold strategy, showing the relative performance of each strategy. Positive values indicate a better performance, while negative values show underperformance relative to the Buy and Hold approach.

2.5 Logarithmic Function

Next, I implemented a logarithmic function, which grows more slowly compared to the exponential function thereby possibly making fewer trades with each being more "certain". The logarithmic trade percentage was calculated as:

$$\text{trade\_percentage} = \log(1 + \text{abs}(m2\_change) \times k)$$

with k as a scaling factor. This strategy aimed to moderate the trading actions, providing a more tempered response to M2 changes. The logarithmic strategy resulted in a portfolio value of approximately $80,452.07, showing better performance than the exponential function but still not optimal.

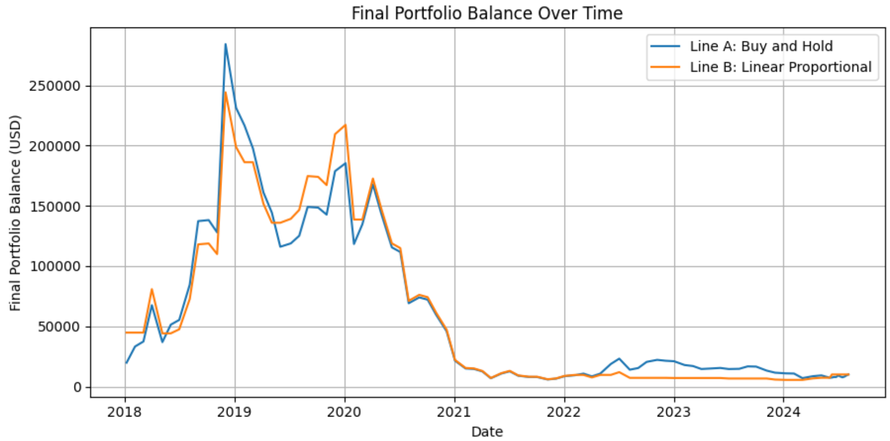

Figure 2: This graph represents the final portfolio balances over time, starting from various dates, for two Ethereum ETH investment strategies: buying and holding ETH (Line A) and a simple trading strategy based on M2 money supply changes (Line B). The x-axis indicates the starting dates for investing or applying the trading strategy, while the y-axis shows the final portfolio balance in USD at the end of the date range. The graph illustrates that both strategies yield similar results, with the simple trading strategy slightly outperforming the buy-and-hold strategy on 52.87% of the dates. The similar mean values and standard deviations indicate that neither strategy has a clear, consistent advantage over the other across the entire time period.

2.6 Polynomial Function

Finally, I implemented a polynomial function, which offered a flexible way to model non-linear relationships. The polynomial trade percentage was defined as:

$$\text{trade\_percentage} = \left(\frac{\text{abs}(m2\_change)}{k}\right)^n$$

where k is a scaling factor and n is the polynomial degree. In my case, I used a quadratic function ($n = 2$), which allowed for a smooth yet significant increase in trade percentage with larger M2 changes. This approach, although among the best trading stragies at a final portfolio value of "\$70,688.98, was still a disaster and likely did not model any relationship grounded in reality.

3 Time-Independence

When a strategy graduates from the gauntlet of the period where it's first studied, it goes to a window outside of it's test. Here, I took the Buy and Hold strategy and the Linear Proportional strategy and graphed what the final portfolio balance would have been on a given day initating the strategy.

The simple trading strategy outperformed the buy-and-hold strategy on approximately 52.87% of the dates. For buy-and-hold, the mean final portfolio value was \$56,682.56 with a standard deviation of \$65,570.16. For the linear proportional strategy, the mean final portfolio value was \$55,679.24 with a standard deviation of \$66,703.88. This near-equal performance suggests that neither strategy has a clear, consistent advantage over the other across the entire date range.

4 Conclusion

The data collected suggest that there is no significant long-term advantage in any trading strategy solely predicated on changes in M2. If there is a direct effect of M2 changes on Ethereum prices, identifying this relationship would require extensive data and complex calculations. Even with these resources, it's unclear whether such a relationship exists. While the initial findings are intriguing, they do not provide a robust basis for a trading strategy that consistently outperforms a simple buy-and-hold approach. The complexities and potential overfitting issues highlighted suggest caution in attributing significant predictive power to M2 money supply changes in the context of Ethereum price movements.