Supply and Demand Levels Forecasting Based on Returns Volatility

Leandro Guerra*

* Outspoken Market, November 2022, updated in September 2025
https://om-qs.com

Abstract — Supply and demand levels—also known as support and resistance—are central to retail trading decisions but are mostly drawn subjectively from charts. This paper proposes an ex-ante, quantitative methodology that identifies and forecasts these zones from each asset's return-based volatility, replacing heuristic markings with rules that are consistent across markets and timeframes. Because levels are computed before the evaluation period (annum/month/week) using a fixed reference date, they are known in advance and can be used to plan entries, exits, and risk limits. The approach is objective, portable across asset classes, and suitable for both discretionary use and as features in systematic models.

Index Terms*- supply–demand zones, returns-based volatility, ex-ante bands, breakout strategies, risk management, quantitative finance.*

I. Introduction and Literature review

Supply and demand—operationalized in trading as support and resistance—are central to price formation in any market. In equities, level-based trading is especially popular among retail investors (Achelis, 2001), who scan for zones where price might react and try to profit from that response. A common approach is the breakout: when price moves through a presumed supply/demand zone, traders enter in the direction of the break. Others attempt to fade breaks, judging them as weak or false using ancillary cues such as volume (AS, 2013).

The core difficulty is that these zones are typically drawn from charts or derived from backward-looking indicators, leaving their identification highly discretionary (Osler, 2000). There is no agreed-upon, pragmatic definition of what constitutes a valid level or a valid confirmation, and candidate conditions are numerous. Unsurprisingly, the profitability of such techniques remains unproven in a robust sense; the literature reports mixed evidence and highlights substantial pitfalls in evaluation (Park, 2007).

A practical way to address the subjectivity problem is to anchor the analysis in return volatility rather than price patterns. The key choice is to compute volatility from returns, not prices. Volatility measures dispersion. If you use prices, the level of the series contaminates the estimate: as the price drifts higher or lower, the same absolute moves imply different "volatilities," and securities with different price scales become incomparable. Returns are scale-free and far easier to compare across assets and horizons. They also tend to be closer to stationary over typical windows, which gives them more convenient statistical properties for inference and forecasting (see Campbell et al., 1997).

If volatility is computed from prices, you cannot consistently compare time frames for a given security, nor can you say how volatile one asset is relative to another. Return-based measures solve both issues because they live on a common scale. Building on this, the paper presents a step-by-step method to identify and forecast supply and demand zones without hand-drawn, discretionary levels. The approach uses each asset's own return volatility to define candidate zones and their expected persistence, and it generalizes naturally across markets.

This updated edition extends the original 2022 study through September 2025 and across multiple assets (Bovespa, S&P 500, and Bitcoin). The core idea is unchanged: use returns-based volatility to project ex-ante Supply & Demand zones and eliminate chart-reading subjectivity. Crucially, all bands are known upfront—at the start of each month or week—because they are computed from a prior reference price and its volatility. That ex-ante construction makes the indicator auditable and trustworthy: no look-ahead, no hindsight tuning.

II. Methodology

It is well established in the literature that volatility is quantified by the standard deviation of returns (equivalently, the square root of their variance) over a specified horizon. Accordingly, volatility for a window T is computed as in Equation (1).

$$vol = \sigma\sqrt{T} \ [1]$$

where:

vol = volatility for an interval of time
σ = standard deviation of returns
T = number of periods in the time horizon

We estimate daily realized volatility with a 20-day rolling window, which approximates one trading month. Annualization follows the square-root-of-time rule (multiply by √252). To express the figure on a monthly or weekly basis, we de-annualize by dividing the annualized volatility by √12 or √52, respectively. For readability, results are reported in percentage points by multiplying by 100. The dataset is from Yahoo Finance (01/01/2012–10/11/2022), and all computations were performed in Python.

For interpretation, we adopt the standard normal-returns approximation as a baseline. Under this convention, one-sigma bands contain roughly 68.3% of outcomes over the stated horizon. For example, an annualized volatility of 15% implies a weekly volatility of 15%/√52 ≈ 2.08%; thus, in a typical week, returns would be expected to fall within ±2.08% about two-thirds of the time. While financial returns often exhibit fat tails and skewness, this approximation provides a useful first-order yardstick; richer, heavy-tailed models can be explored in future work.

With the volatility estimator defined, we specify supply and demand zones as volatility-anchored bands around a chosen reference price P_{ref} observed on date t_0. For a horizon H (e.g., 1 year or 1 week), let $\sigma_H$denote the return volatility at that horizon (computed from returns, not prices). Assuming zero drift over H, the 1-sigma bands are:

Annual bands (1y)

$$Supply_{1y} = P_{ref}(1 + \sigma_{1y}) \ [2]$$
$$Demand_{1y} = P_{ref}(1 - \sigma_{1y}) \ [3]$$

Weekly bands (1w)

$$Supply_{1w} = P_{ref}(1 + \sigma_{1w}) \ [4]$$
$$Demand_{1w} = P_{ref}(1 - \sigma_{1w}) \ [5]$$

These multiplicative bands provide an objective, scale-free way to locate candidate supply/demand zones without discretionary drawing. If a wider or narrower confidence envelope is desired, a scalar $k \geq 0$ can be applied, yielding $P_{ref}(1 \pm k\sigma_H)$ (e.g., k=2 for a ~95% band under the normal-returns approximation).

For illustration, consider Case A (annual bands). Take the last trading day of 2021 as the reference date and record its reference price and annualized return volatility. Plug these into Equations [2] and [3] to obtain the projected supply and demand bands for 2022. The same procedure applies to Case B (weekly bands) or any other horizon, provided you use the volatility at that horizon and the corresponding formulas. If a wider confidence envelope is desired, use a k-sigma band: replace σ_H with kσ_H. For example, k=2 approximates a 95.45% range under the normal-returns baseline. Equations [6] and [7] show this extension for Case B, which we discuss in detail in the results section.

$$Supply_{1w2d} = P_{ref}(1 + 2 * \sigma_{1w}) \ [6]$$
$$Demand_{1w2d} = P_{ref}(1 - 2 * \sigma_{1w}) \ [7]$$

The choice of annual or weekly horizons, and of 1- or 2-sigma bands, should be set by the investor according to risk tolerance, decision horizon, and the intended strategy. These parameters are design dials: select the horizon that matches how often you act, and the sigma width that matches how much adverse movement you are willing to tolerate.

III. RESULTS

We begin with annualized volatility. Figure 1 reports the series for the S&P 500 (^GSPC), and Figure 2 reports the series for the Ibovespa (^BVSP), Brazil's benchmark equity index.

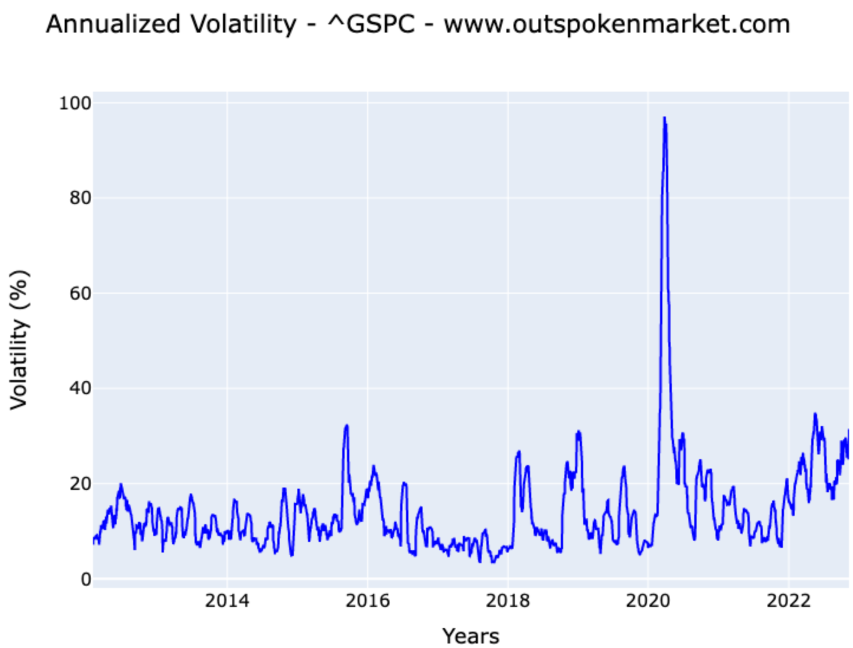

Figure 1 - Annualized volatility for S&P500

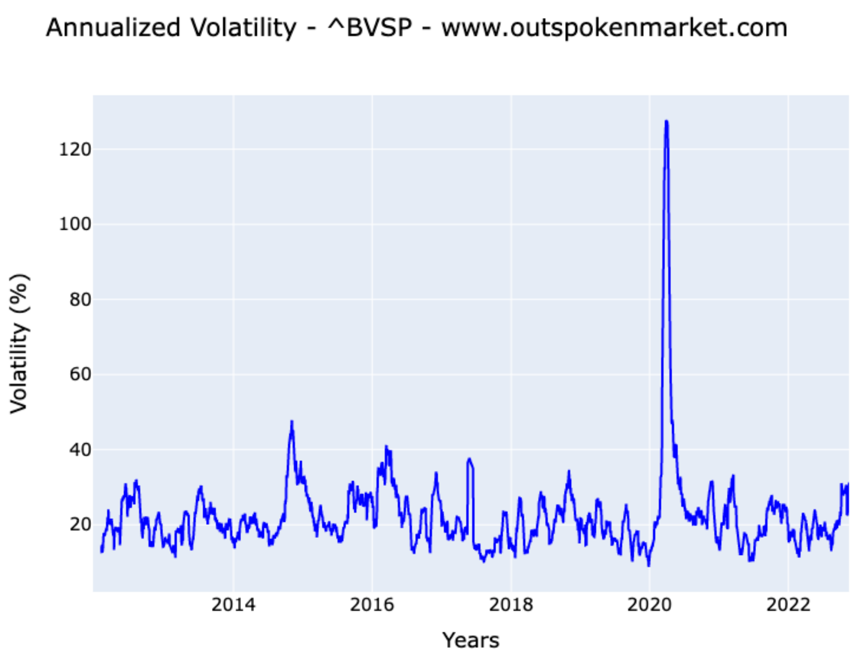

Figure 2 - Annualized volatility for Ibovespa

The key point is that, because volatility is computed from returns, the values are directly comparable across indices. At the onset of COVID-19 in early 2020, the Ibovespa's annualized volatility rose above 120%, while the S&P 500 peaked near, but below, 100%. Next, Figures 3 and 4 show, for the S&P 500 and the Ibovespa respectively, an example of Case A: annual volatility-anchored supply and demand bands.

Figure 3 – 2022's annual supply and demand volatility zone for S&P500

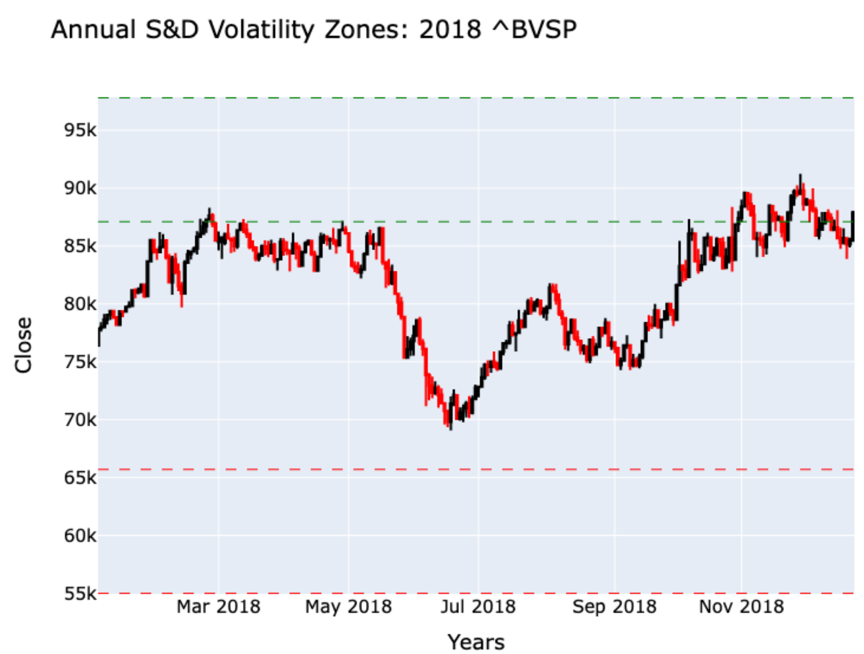

Figure 4 – 2018's annual supply and demand volatility zone for Ibovespa

The periods shown were selected to best illustrate the proposed method and to provide an ex-ante demonstration of its forecasting use: in each case, subsequent price action clustered around bands that were computed ahead of time. Finally, Figures 5 and 6 present Case B (weekly bands) for the S&P 500 and the Ibovespa, respectively, with a focus on 2022 to enhance readability at weekly granularity. Both charts demonstrate also the 2 standard deviation levels.

Figure 5 – 2022’s weekly supply and demand volatility zones for S&P500

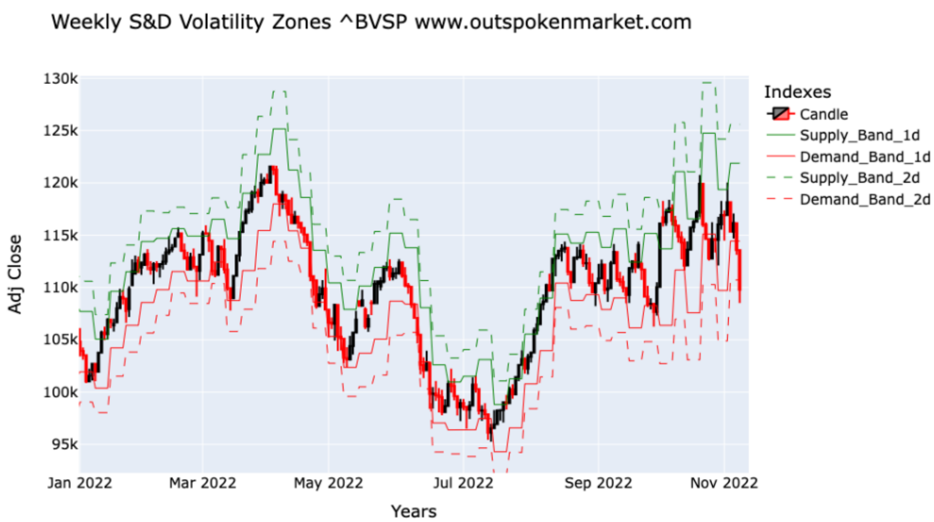

Figure 6 – 2022’s weekly supply and demand volatility zones for Ibovespa

Since the original paper (2022), we’ve kept the same rules and pushed them forward in time. Figures 7–9 (September/2025 snapshots from OMQS) show the monthly Supply & Demand Volatility Zones derived from returns-based volatility for the Bovespa, the S&P 500, and—added as a cross-asset check—Bitcoin. Across these very different markets, the ex-ante bands (built from prior-period reference price and volatility) continued to frame price action: tests, pauses, and accelerations tend to cluster around the 1σ/2σ demand and supply corridors. You’ll see stepwise shifts when volatility regimes change, and those steps often precede the next range the market explores, which is precisely the forecasting value we argued for in 2022.

What began as a research note is now a live, free tool at Outspoken Market Quant Services (OMQS) — om-qs.com. The platform computes these zones daily for multiple assets, always using only information available at the time, so you can validate the method yourself and use it to plan entries, exits, and position sizing. It’s not a crystal ball; it’s a robust, scale-free framework for risk and context that has held up over years and across asset classes.

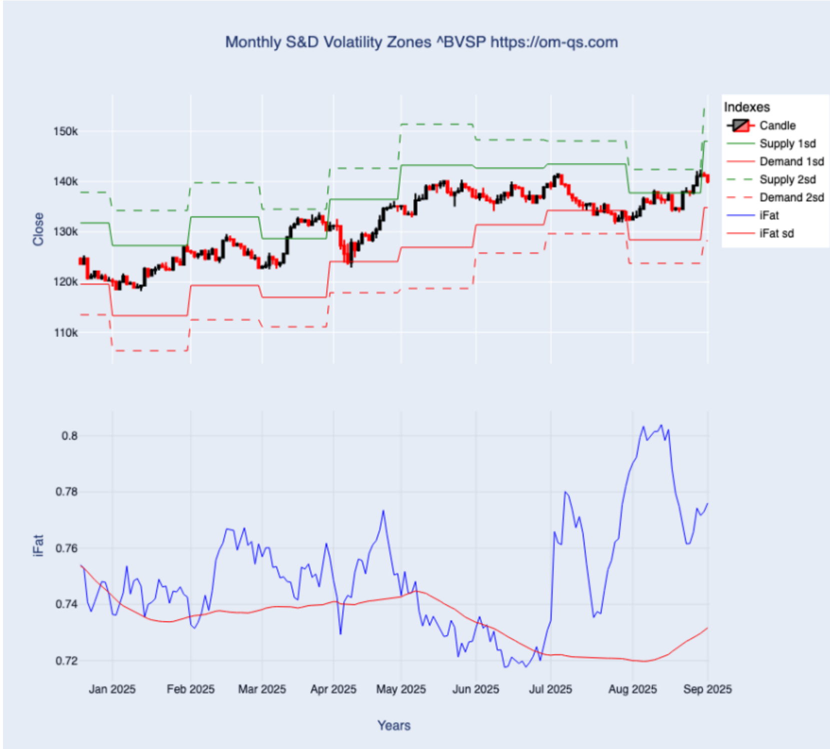

Figure 7 – 2025's monthly supply and demand volatility zones for Ibovespa

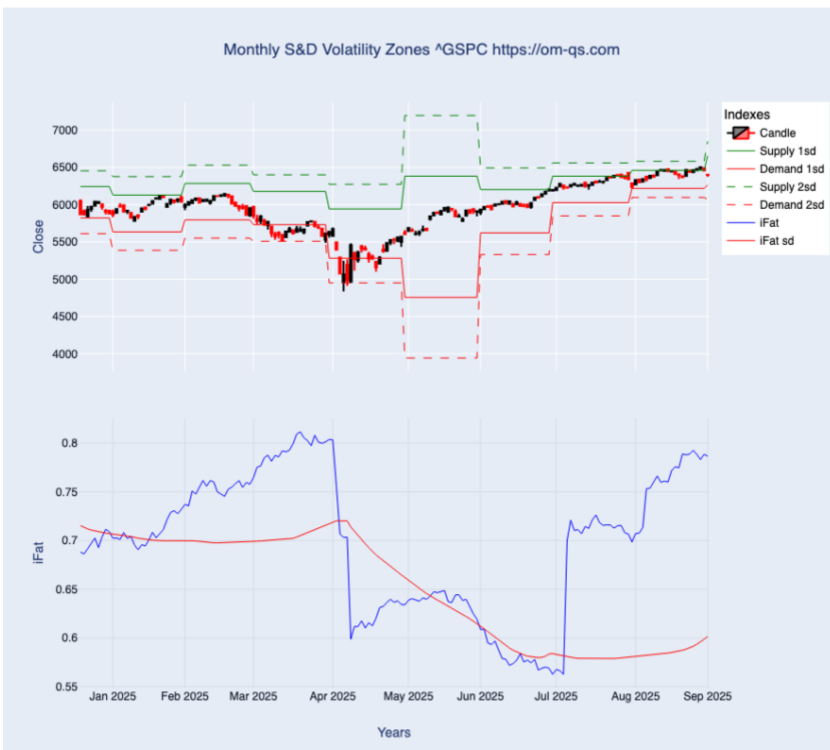

Figure 8 – 2025's monthly supply and demand volatility zones for S&P500

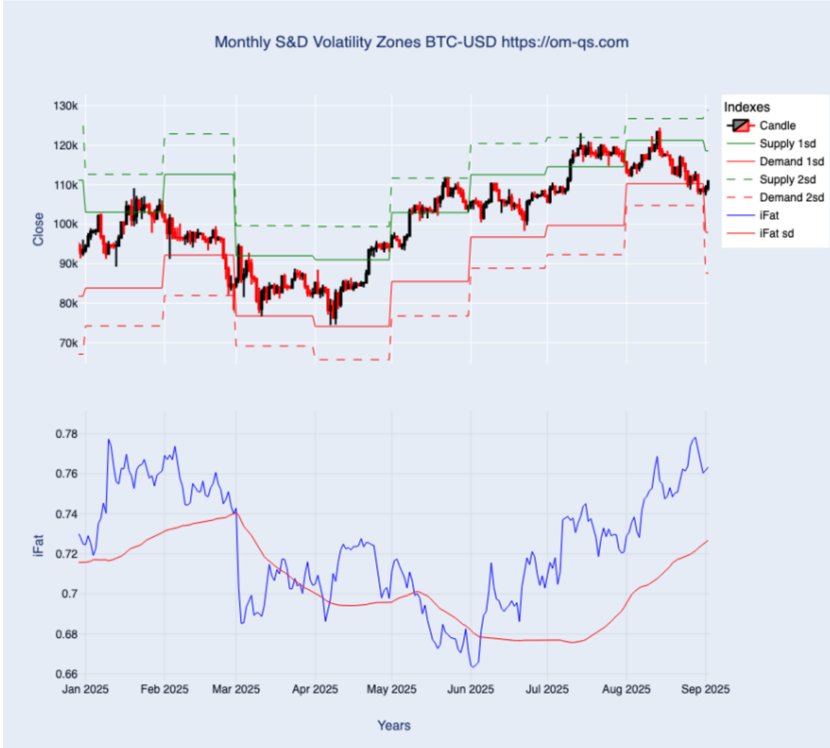

Figure 9 – 2025's monthly supply and demand volatility zones for Bitcoin/US Dollar

Note: the iFat indicator shown in the updated figures is outside the scope of this paper and is therefore not discussed here; a practical walkthrough is available on the Outspoken Market YouTube channel.

IV. Conclusion and Discussion

This paper introduces a quantitative, pragmatic framework for forecasting supply–demand zones by projecting levels from returns-based volatility in a forward-looking manner. The goal is to strip out chart-reading subjectivity and make the process auditable and repeatable. While the method is usable by any market participant, it is especially intended to empower retail investors—who typically lack the technical and financial infrastructure of institutions—with high-quality, ex-ante reference levels for decision-making.

A wide range of approaches can benefit from these zones. Classic breakout systems can use them as objective triggers or targets, while machine-learning pipelines can ingest them as structured features (e.g., distances to bands, touches, and breaches) to improve model context. This opens clear avenues for future work: measuring the incremental performance of strategies that incorporate the zones, and evaluating the zones' behavior as a standalone decision aid under different regimes.

Our three-year out-of-sample extension (through September 2025) shows that volatility-derived bands remain a robust contextual tool: prices repeatedly interact with the pre-announced levels, aiding entries, exits, and sizing. The approach's strength lies in its transparency—levels are fixed before the week or month begins—and its portability across markets. We recommend using the zones as an objective risk framework, not a solitary signal, and combining them with regime filters. Live, free calculations are available at OMQS (om-qs.com), enabling independent verification and practical adoption.

REFERENCES

Achelis, S. B. (2001). Technical Analysis from A to Z.
Osler, C. L. (2000). Support for resistance: technical analysis and intraday exchange rates. Economic Policy Review, 6(2).
AS, S. (2013). A study on fundamental and technical analysis. International Journal of Marketing, Financial Services & Management Research, 2(5), 44-59.
Park, C. H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis?. Journal of Economic surveys, 21(4), 786-826.
Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The Econometrics of Financial Markets. Princeton University Press. https://doi.org/10.2307/j.ctt7skm5

AUTHORS

Leandro Guerra – MSc in Finance and Investment Management (University of Salford, UK), founder of the Outspoken Market, Head of Data Science and Analytical Platforms for Experian EMEA/APAC. E-mail: leandro.guerra@outspokenmarket.com