FIN9007 Derivatives 2025

Group Project

S&P 500 futures and options: analyses and practice

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1.1

	S&P500	**SPDR ETF**	**E-Mini**	**SPX Options**	**SPY Options**
Mean	0.1091132	0.1086687	0.08229747	-0.00007532506	-0.00008622601
Variance	0.0001223562	0.0001198561	0.0003424055	0.7274462	3.874717
St. Dev.	0.1755955	0.1737922	0.2937451	0.8529045	1.96843
Skewness	-0.8640763	-0.856228	-0.8022163	0.04022248	-0.04831184
Kurtosis	19.34186	17.18241	14.28098	128.24	17.20126
IQR	0.11233	0.105	0.108524	0.07854	0.104555
Min	-0.13131	-0.11958	-0.116665	-11.636045	-10.943923
Max	0.09334	0.09042	0.100465	11.736869	11.044664

The S&P 500, SPDR ETF and E-mini futures exhibit similar average returns, indicating that they closely aligned in terms of central tendency. This suggests that both the ETF and futures effectively track the underlying index over time. In contrast, the SPX and SPY options display mean returns which are effectively zero, reflecting their nature as derivatives instruments whose values are not driven by broader directional trends but by fluctuations in the underlying assets. Overall, the return distributions differ markedly in location, with options centred near zero, while the index, ETF and futures exhibit a positive average return.

The E-mini futures exhibit noticeably higher variance in returns compared to the S&P 500 and SPDR ETF, indicating greater volatility which is typical of leveraged instruments and extended trading hours. In contrast, the SPDR ETF mirrors the index closely, with both showing tightly clustered returns around the mean, consistent with their low variance. SPX and SPY options display markedly greater dispersion, indicative of the higher inherent volatility in options markets. Their returns distributions are broad and centred near zero, with extreme variability driven by sensitivity to strike, time to expiry and implied volatility. These patterns highlight the distinct risk profiles across instruments, with options exhibiting the highest standard deviations.

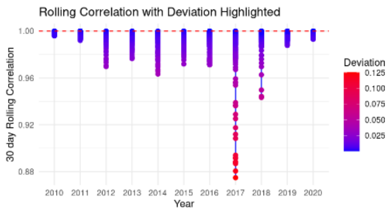
The S&P 500, SPDR ETF and E-mini futures all exhibit negative skewness, consistent with the typical asymmetry observed in equity returns where sharp downside movements are more common than upside gains. In contrast, the SPX and SPY options display near zero skewness, suggesting more symmetric return distributions – empirically a result of option pricing dynamics, particularly for contracts which are near the money. Kurtosis further differentiates these instruments with underlying assets exhibiting elevated but controlled kurtosis, indicating distributions with moderate tail risk. Meanwhile, SPX and

SPY options show extreme kurtosis, marked by their concentrated return distributions around zero with infrequent but substantial outliers. This reflects the typical profile of options, where prolonged periods of price stability are disrupted by rare, large moves, driven by shifts in volatility, moneyness or time decay.

The IQR is similar across assets (~0.105 to 0.112), suggesting that the middle 50% of daily returns exhibit similar dispersion. The minimum return is lowest for the S&P500 at -13.13%, indicating the index has experienced larger negative outliers than the other two. The maximum return is slightly higher for the E-Mini (10.05%), which might reflect its higher intraday volatility. SPX options have an IQR of 0.07854, reflecting moderately narrower clustering of changes for typical observations, while still having the potential for significant outliers. SPY options (0.104555) mirror the underlying assets more closely, though their higher variance warns of frequent large deviations outside that middle range.

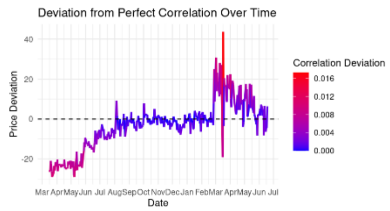
1.2

Given the SPDR ETF is a tracker of the S&P500 index, we would expect the correlation between the two daily prices to be equal to 1, but it is 0.9999867, this is visualised in Appendix 1.2.A and 1.2.B. 1.2.C shows us when the tracking errors were greatest using a 30-day rolling correlation, which we see to be 2017. This could be due to; the low volatility at the time (limiting the actions of arbitrage traders), record ETF inflows (temporarily distorting pricing), high dividend payouts (intensifying a cash drag). These tracking error examples tie back to the liquidity of the fund and how it affects their ability to rebalance their portfolio in line with index movements.



1.2.C; 30 Day rolling correlation visualisation shows us during what year tracking errors were greatest.

The correlation coefficient for the price of S&P 500 futures contracts and the index itself is 0.9979599. This is visualised in Appendix 1.2.D, with 1.2.E attempting to show at which prices this deviation was further from 1. 1.2.F shows us when the tracking errors were greatest, which we see to be March, around the start of the COVID-19 pandemic. This is likely due to the decreased trading hours and higher levels of uncertainty as the world was trying to grasp a completely new phenomenon.



1.2.F; Deviation by year from perfect correlation between the index and futures prices.

2.1

This study estimates the underlying asset price implied by put-call parity using SPX options data from January 10, 2020. It compares the parity-implied value to the actual S&P 500 index level and futures price, derives the implied interest rate and dividend yield, and evaluates whether the implied price consistently moves in the same direction as the index.

1. Estimating the Put-Call Parity Implied Underlying Price - Based on a range of call and put option prices across strike levels, the put-call parity implied S&P 500 index price was computed using the standard parity relationship expressed as: $S_{PCP} = C + Ke^{-rT} - Pe^{-qT}$. The estimated implied price on the given date was computed as 3265.35. This precisely matches the actual closing level of the S&P 500 index, also 3265.35, indicating near-perfect alignment between market option prices and the underlying asset's spot value.

2. Comparison with S&P 500 Futures Price – The implied asset price was next compared to the S&P 500 futures price for the same expiration date. The futures contract too traded at 3265, showing extremely close correspondence to both parity-implied price and the spot index level. This consistency confirms that the spot, futures, and options markets were efficiently price and harmonious, as is expected under no-arbitrage conditions.

3. Implied Interest Rate and Dividend Yield – Computing using the adjusted parity relationship, the implied risk-free interest rate was derived at 1.88% and the implied dividend yield as 1.83%. These when assessed with market benchmarks at the time such at the U.S. Treasury yield curve, indicated 1.5 – 1.8% for comparable maturities, while the S&P 500's historical dividend yield ranged from 1.5-2 %. This indicates that option prices reflect not only underlying asset values but also realistic macroeconomic expectations.

4. Directional Consistency with the S&P 500 – To assess whether the put-call parity implied asset price consistently moves in the same direction as the S&P 500 index, several tests were conducted. Firstly, the percentage deviation between the implied and actual index prices was found to be at 0%, depicting perfect alignment. Secondly, the standard deviation of implied prices across multiple strikes returned a value of 0.2337, indicating high clustering and pricing consistency. Thirdly, cross expiry comparison showed that standard deviations remained low across multiple expiration dates, with all values below 0.25. In addition, the distribution of implied prices was unimodal and sharply peaked near the index level (Appendix 2.1), suggesting limited dispersion and thus, high pricing precision. These results confirm that the parity-implied asset price closely tracks and

moves in line with the index, exhibiting no significant divergence over time or across strikes. The analysis validates put-call parity, with the implied price aligning closely with the index and futures, and minimal deviation across strikes or time, consistent with prevailing rates and yields.

2.2

A direct comparison between the theoretical option price bounds and observed market prices confirms all call and put options lie strictly within their respective no-arbitrage limits. These bounds, derived from fundamental pricing principles, define permissible ranges within which market prices must fall to prevent arbitrage opportunities. Visual inspection of plotted market prices against their upper and lower theoretical bounds (Appendix 2.2) shows no violations, with no price breaches across any strike levels, indicating conformity with underlying pricing constraints. This indicates that market participants are correctly pricing options in line with intrinsic value, time value and cost-of-carry. Additionally, the put-call parity implied underlying price closely aligns with the actual S&P 500 index level and futures price, with negligible deviations, low dispersion, and tight clustering across strikes – signalling pricing consistency in options market. These findings indicate that option prices not only respect theoretical pricing limits but also incorporate justified expectations of interest rates and dividends. Since no deviations or pricing anomalies are detected, the analysis provides strong evidence that there were no arbitrage opportunities in the market. Thus, we conclude that market efficiency has been upheld relative to the pricing of options on the given trade date.

3

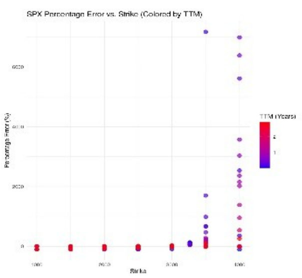
SPX: We used a 1000-step binomial tree to calculate theoretical prices for SPX options as of 10 January 2020. The model assumed 20% volatility, a 5% risk-free rate, and a 2% dividend yield. The spot price was set to 3265 to match the SPX close on the trade date. The model was applied across a range of strikes on either side of the underlying and used all available maturities. For each option, we computed the model price and compared it to the market price using absolute and percentage deviations. Results were generally accurate for at-the-money and longer-dated options. However, short-dated, high-strike options showed substantial errors – at times exceeding 7000% - driven by the model overpricing deep out-of-the-money calls with very low market values. Even small absolute differences in this region result in large percentage errors.

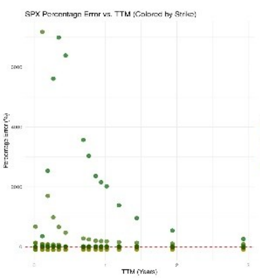
To confirm the reliability of these results, we verified that calls and puts were correctly flagged, expiry dates were valid, and model internals like the risk-neutral probability (pCRR) remained stable. This confirmed that pricing deviations were a result of model assumptions and not coding issues.

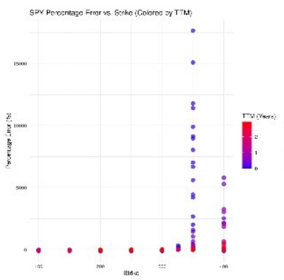
SPY: We repeated the analysis for SPY options, adjusting the spot price to 326.5 to reflect its 1/10 relationship with SPX. The same model parameters and strike ranges were used. The results closely mirrored SPX. The model priced near-the-money and long-dated options well, but significantly overestimated prices for short-dated, high-strike calls - particularly above strikes of 300 - where market values were often near zero. This led to extreme percentage errors, with the largest exceeding 17,000%. These patterns reflect the constant volatility assumption failing to capture the implied skew in the market.

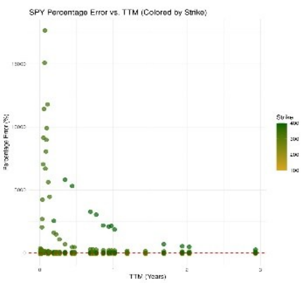
Visualisations: We produced four visualisations - two per asset - showing percentage error against strike (coloured by time to maturity) and against time to maturity (coloured by strike). These revealed consistent patterns.

For both SPX and SPY, large errors appear only in high-strike options with short maturities, while lower strikes show small or no errors. Errors reduce rapidly beyond one year to expiry and are minimal by the 2–3-year range. The plots confirm that the model performs well near the money and over longer horizons, but breaks down at the extremes, where market pricing reflects volatility skew and sharper time decay (higher theta sensitivity).









Conclusion: The binomial tree model offers a systematic approach to option pricing, but its limitations explain many of the deviations we see from market prices. Notably, it assumes a fixed volatility, whereas real markets exhibit skew and smile patterns that vary by strike and maturity. The model also ignores microstructure effects like bid-ask spreads, which can distort observed prices - especially for low-value, short-dated options. As a result, while the model is broadly consistent with market prices for near-the-money and longer-dated options, it overestimates prices for short-dated, high-strike contracts, leading to large percentage errors. To improve consistency with market pricing, implied volatility could be incorporated or using more advanced frameworks. We could also filter out very low-priced options to help reduce errors.

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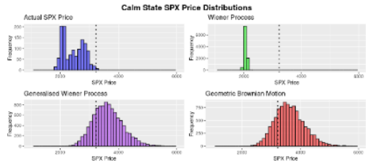
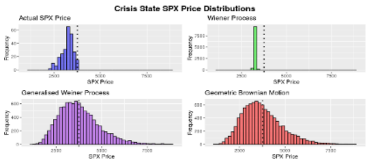


4.A; Calm State Distribution at Expiry for; SPX, WP, GWP, GBM.



4.B; Crisis State Distribution at Expiry for; SPX, WP, GWP, GBM.

To examine model behaviour under distinct market conditions, the sample was split into two periods, 2015 – 2019 and 2020 to reflect a calm vs crisis states respectively. As we can see, both state's Weiner processes (WP) predict a value equal to that at the start of each observed period, given the lack of a drift term and variance with a mean of 0. The Generalised Weiner Process (GWP) and Geometric Brownian Motion (GBM) simulations both do a better job of depicting the stock price at expiry with the latter being more accurate during the crisis period as the GWP has likely simulated negative prices.

The variance is underestimated in the WP, given its lack of account for a drift term. With GWP and GBM, variance is consistently overestimated, which we can expect as these stochastic simulations account for extreme circumstances despite them more unlikely in the observed index movement. Regarding skewness and kurtosis, none of the model's predictions align perfectly with the observed index movement however provide good estimates for the upper bound of risk and variation within the market, making them useful tools despite not describing the index relatively accurately.

The GWP falls short of the GBM as it has the potential to simulate negative prices, which we know to be impossible in the real world. Observing from the table (Appendix 4), the GWP has a high standard deviation (1129.38) and positive skew (0.9012), indicating that negative values are likely to have been simulated, making it less accurate than the GBM at describing the S&P500 index movement during these periods.

Overall, the order of how well these stochastic processes describe the movement is as follows, (worst to best); WP, GWP, GBM. Each of the models builds on ideas presented by the prior but makes corrections to allow for a higher level of accuracy and unison with how the real price behaves.

5

SPX European calls were quoted by three models: Black-Scholes-Merton (BSM), Monte Carlo simulation, and Geometric Brownian Motion (GBM), utilizing January 10, 2020-

based parameters (spot price: 3265.35, risk-free rate: 1.88%, dividend yield: 1.83%, volatility: 20%).

Call prices estimated by BSM were well consistent with market prices of deep in-the-money strikes. For example, the 800-strike call had a BSM price of 2444.99 compared to a market price of 2445.00—a virtual zero deviation (see Table 5.1). However, model underpriced out-of-the-money puts. Strikes of 800–1200 were quoted near zero (10^{-24} to 10^{-12}), whereas actual market prices ranged from \$0.05 to \$0.15 (Table 5.2). This reflects BSM's limitations; constant volatility assumptions and inability to capture downside risk inherent in the market through volatility skew.

Table 5.1: Black-Scholes vs Market Price – Call Options

Strike	*Market Price (Call)*	*BSM Price (Call)*
800	2,445.00	2,444.99
900	2,345.75	2,345.85
1000	2,247.00	2,246.70
1100	2,147.65	2,147.56
1150	2,097.95	2,097.98
1200	2,048.55	2,048.41

Table 5.2: Black-Scholes vs Market Price – Put Options

Strike	*Market Price (Put)*	*BSM Price (Put)*
800	0.05	2.228647×10^{-24}
900	0.05	1.676607×10^{-20}
1000	0.08	2.617535×10^{-17}
1100	0.15	1.214848×10^{-14}
1150	0.13	1.804120×10^{-13}
1200	0.15	2.164554×10^{-12}

Monte Carlo simulation (10,000 iterations) priced the 1425-call at 1820.76, close to BSM and market prices, validating the model under risk-neutral assumptions. The same simulation, however, returned a put option price of zero since not a single path simulated was below the strike. This highlights the weakness of terminal-only payoff models in scenarios with rare but significant tail risk.

GBM simulation, executed with 252 steps, delivered greater realism by capturing intraday price paths. The 1425-strike call cost 1825.88, essentially the same as BSM and Monte Carlo, while the put returned a far more realistic 15.08. Path-dependency inherent in GBM allowed it to register intermediate price dips, which more accurately reflected actual market sentiment.

Model prices across strikes are shown in Appendix 5. All the methods converged around at-the-money and in-the-money strikes. Divergence picked up in deep out-of-the-money puts, further indicating the role of modelling assumptions. Overall, BSM remains a good benchmark for calm markets, but GBM and Monte Carlo give more flexible pricing models, specifically in terms of capturing skew, tail risk, and volatility dynamics.

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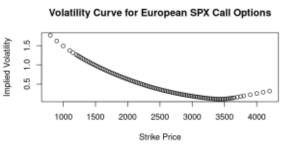
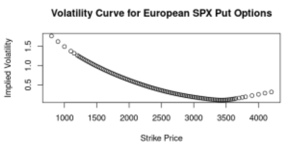
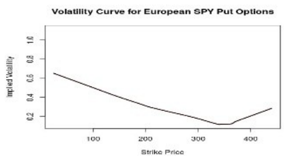


6.A; European SPX Call IV Plot



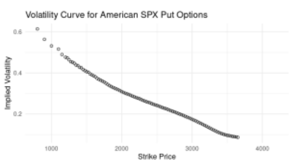
6.B; European SPX Put IV Plot

6.C; European SPY Call IV Plot



6.D; European SPY PutIV Plot

All these curves exhibit a volatility smirk, and we observe implied volatility being the lowest when the strike price is closest to the underlying price as traded on 10/01/2020. Overall, this is expected, as the OTM and ITM options have higher implied volatility than ATM options. This aligns with theory, as the higher volatility for strikes further from underlying are driven by hedging and speculative trading strategies. Given that the interest rate used is implied from the put call parity, the SPX Call and SPX Put charts are identical. The SPX curves have a slightly right skew, possibly due to the log-normal identity of the Black-Scholes pricing model compared with the observed market prices, but could also mean the overall market sentiment was that prices will go up in the future, given that implied volatility is lowest for a price around \$3400, i.e. the market predicts growth to around \$3400 by the expiry date, 20/06/2020, driving its low implied volatility. We observe a higher volatility for SPY than SPX, despite the curves showing a similar shape, because SPX options are traded in higher volumes by institutional traders, which, with the increased level of market information, force volatility to decrease. Another possibility for the higher volatility in SPY options is that the nature of retail traders means that more speculative trades will take place, pushing up the volatility.



6.E; American SPX Call IV Plot

6.F; American SPX Put IV Plot

6.G; American SPY Put IV Plot

6.H; American SPY Call IV Plot

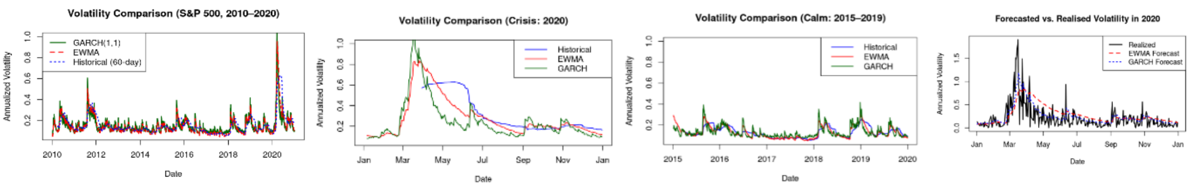
As we see from both SPX and SPY implied volatility curves for American put options, they both exhibit the classic smile/smirk. This highlights that ATM options have the lowest implied volatility and the further away from this, the higher the implied volatility is, as aligning with empirical evidence.

For American call options, the curve is steeper, with no options being sold at a price lower than $2425 for SPX and $205 for SPY, likely due to the market sentiment that prices will not drop below these prices, hence it is not worth the payoff for anyone to sell an option at this strike price. However, they still exhibit the classic smile, aligning with theory that ATM options have the lowest volatility.

Realised Volatility (RV) refers to the “true” volatility observed in realised historical prices, essentially a measure of how the underlying asset has changed over time. Conditional Expected Volatility (CEV) is calculated using models such as GARCH and estimates future volatility based on past prices and recent shocks. Implied Volatility (IV) refers to the volatility that when implemented into pricing models, equates market and model prices, reflecting market expectations of future volatility.

RV and CEV are similar in that they are both calculated from past price datasets; however, CEV aims to predict volatility in the future whereas RV simply calculates how the prices have behaved in the time up to calculation. If there is greater uncertainty at the time of calculation than the RV window, IV will be higher than realised, and vice versa. IV and CEV both aim to measure future volatility and are often very close in measure but can differ significantly when market expectations rapidly change. CEV is purely based on historic price data and fails to account for market expectations of the future whereas IV considers market prices of options, which have investor expectations incorporated into its calculations. IV is often higher than RV, given that its forward-looking and sentiment driven approach demands a premium for the unknown risk associated with market movements.

7.1



7.1.A - Volatility estimates from Historical, EWMA, and GARCH models (2010–2020). Comparison of S&P 500 volatility using a 60-day rolling window, EWMA (λ = 0.94), and GARCH (1,1) over the full sample. GARCH captures volatility clustering and persistence, while historical volatility lags in responsiveness.

***7.1.B and 7.1.C**; contrast model behaviour across calm and crisis regimes, showing that while all models remain stable in low-volatility periods, GARCH and EWMA respond more swiftly and intensely during market shocks than historical volatility.*

7.1.D - Forecasted vs. realized volatility in 2020. One-step-ahead volatility forecasts from GARCH and EWMA compared to realized volatility (squared daily returns). GARCH tracks realized volatility more closely throughout the crisis, resulting in lower forecast error.

Volatility in the S&P 500 index from 2010 to 2020 was examined using three models: a 60-day rolling historical volatility estimate, an EWMA model and a GARCH (1,1) model.

Historical volatility reflects past variability with a fixed window and shows sluggish response to sudden market shits. In contrast, EWMA adapts more quickly by weighting recent returns more heavily, whilst GARCH provides the contextually most dynamic and persistent estimates, effectively capturing volatility clustering. A visualisation depicts that all models detect major stress events – especially for 2020 – but differ in responsiveness as expected. To examine these behaviours more closely, the sample was segmented into a calm period (2015 -2019) and a crisis period (2020). This regime-based comparison revealed further contrast in model performance: GARCH being most sensitive to short-term fluctuations and persistent, EWMA moderately adaptive and historical volatility lagging during shocks, in the context of this analysis. In the crisis period, GARCH responds most aggressively to the volatility shock and reflects a gradual decline afterwards, mirroring closely the dynamics of the actual market. EWMA also responds swiftly but remains elevated longer, reflecting its slower decay. Historical volatility increases with markedly significant lag, underestimating the severity and timing of the shock. Overall, while historical volatility offers a stable benchmark, conditional models – particularly GARCH- deliver more accurate, timely reflection of evolving market risk.

7.2

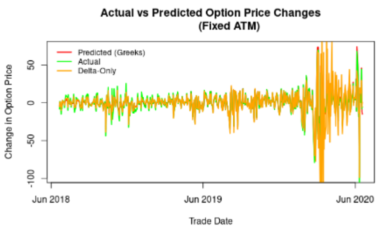
We also compare the forecasting performance of GARCH (1,1) and EWMA models for S&P 500 volatility using one-step ahead forecasts throughout 2020. Both models were estimated on daily data from 2010-2019 and evaluated against realised volatility, which are proxied by squared daily returns. This approach enables a practical assessment of how each model anticipates evolving risk under volatile market conditions. A plot comparing the annualised volatility forecasts from GARCH and EWMA against realised volatility, shows that both models responded to the volatility spike in March 2020, but differed in their ability to track the subsequent market dynamics. GARCH captured both the rapid rise and the decay of volatility more accurately, while EWMA remained elevated for longer. This is also reflected in lower RMSE values for GARCH comparatively, indicating superior predictive accuracy. This behaviour is consistent with theoretical and structural differences: GARCH accounts for both recent shocks and past volatility persistence, whilst EWMA applies exponential weighting without explicitly modelling volatility clustering. Overall, both are viable, but GARCH being more accurate and responsive in measuring conditional volatility during periods of heightened uncertainty making it more effective for applications in risk management, value-at-risk estimation or trading strategies – wherein timely and precise volatility estimates are critical – making it the more robust tool for such forecasting, as supported by both quantitative and visual metrics.

8

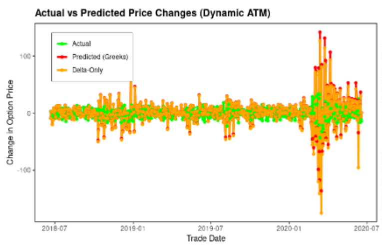
This analysis explores how the price of an ATM SPX call option changes over time and assesses whether the Greek letters explain those changes effectively. Two approaches have been used: one with a fixed ATM strike and one where the ATM strike is dynamically selected on each trading day to match the prevailing spot price, ensuring the contract remains at-the-money, reflecting prevailing market conditions.

Fixed Strike: A call option with a strike of 3000 was selected as the initial ATM contract. Figure 8A compares the actual option price changes (green) with the changes predicted using a full set of Greeks (red) and a delta-only model (orange). The full Greek based model provides a significantly closer fit to the actual price behaviour, particularly as the option approaches expiration with increased volatility. This closer fit is driven by Gamma capturing curvature in the price path, Vega accounting for shifts in implied volatility and Theta modelling the gradual degrading effect of time decay. The predictive performance of the Delta-only model is inferior comparatively, especially during periods of increasing volatility. This highlights the relevance of Gamma, Vega and Theta in capturing non-linear price effects and time decay.

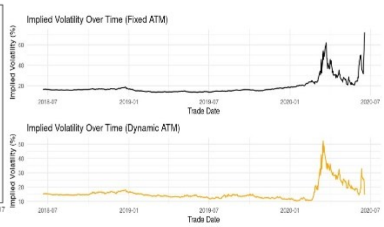
Dynamic ATM Extension: The explanatory power of the Greeks remains strong even in this case. As seen in Figure 8B, the model captures price changes far more accurately than the Delta-only model, particularly during heightened market stress such as early 2020. We observe, predicted price changes using Vega and Gamma Diverge significantly from the Delta-only trajectory and align more closely with actual option prices. Furthermore, implied volatility rose notably during these events, increasing option premiums. Plot 8.C shows the successful capturing of this spike by the Greek based pricing model. Therefore, the Greeks offer a comprehensive framework for explaining option price behaviour. While Delta provides a baseline sensitivity to the underlying, it fails to capture second-order risk (Gamma), volatility exposure (Vega), and time decay (Theta). The analysis shows that in both static and dynamically adjusted ATM scenarios, Greek-based models accurately explain and predict option price movements (See Appendix 8D for supporting Greek sensitivity plots). Notably, this predictive performance is achieved despite limitations of the theoretical frameworks underlying the analysis, i.e. Black-Scholes, which assumes constant volatility and log-normal returns. While the model is limited in capturing comprehensive market complexities, it is still highly effective in analysing the observed sample. Furthermore, although the Greeks are treated individually for the purpose of this analysis, their effects usually are interdependent, accounting for which can result in heightened accuracy.



8.A Actual vs Predicted Option Price Changes (Fixed ATM).
Comparison of realised option price changes with model predictions using a full set of Greeks (red) and a Delta-only approximation (orange), based on a fixed strike of 3000. The full Greek model more accurately captures volatility-induced deviations from Delta predictions.



8.B Actual vs Predicted Price Changes (Dynamic ATM).
The ATM strike is updated daily to match the underlying price. The Greek based model continues to outperform Delta-only predictions, particularly during volatility spikes such as early 2020.



8.C Implied Volatility Over Time (Fixed and Dynamic ATM).
Top: Implied volatility over time for the fixed 3000-strike option.
Bottom: Implied volatility under dynamically selected ATM strikes. Both exhibit sharp increases during early 2020,

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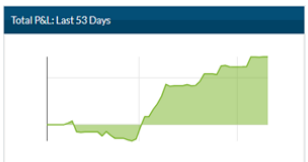


9.A; 53 Day P&L Visualisation

9.B; Movement of S&P500 Futures Prices

9.C; Daily Portfolio Returns

9.D; Cumulative Position

As a group of 4 with varying levels of trading experience, we each employed our own individual strategy. Only one of these was profitable during the time horizon of the challenge, and so our analysis will centre around it. At the end, we will provide commentary on our experiences and lessons learned from all strategies. Over the course of the CME Trading Challenge (29 Jan – 2 Apr), I actively managed a portfolio consisting exclusively of S&P 500 E-mini futures. Starting with $1,000,000, I ended the challenge with a portfolio value of $1,726,487, achieving a total return of 72.65%. For comparison, the S&P500 lost 6.15% over the same period. We began the challenge with a few consecutive losses, but reduced position size and managed risk to limit further downside. Over the period, the cumulative return relative to peak notional exposure peaked at 240.70%. Strong returns were achieved relative to our exposure, with some significant intra-day drawdowns, but daily profit-and-loss (PnL) remained strong throughout. Figure below shows that we achieved positive returns on almost every trading day after the initial week. The goal was to secure small wins and minimize losses while waiting for more favourable situations and asymmetric returns.

9.E; Visualisation of Strategy

9.F; Further Visualisation of Strategy

The annualized Sharpe ratio was 3.60, indicating exceptionally high risk-adjusted returns. This result reflects the fast-paced scalping strategy employed, and the fact that this was achieved over a relatively large sample size of 1,205 trades is promising - perhaps indicating a viable edge. We may, however, expect this to decrease with time, a larger sample, or when using real money.
Beginning the challenge, my expectation was for the S&P 500 index to reach its peak just above 6100. This level had remained difficult to break for many weeks, and so I was biased toward shorts. Many students expected the S&P to continue higher, with year-end targets in the $6500+ area. Regardless of whether these predictions turn out to be correct, there is a lot of time between now and the end of the year. In my view, the risk appeared to be to the downside, remaining volatile due to ongoing macroeconomic developments. I do, however, believe it is a mistake to have conviction on market direction, especially when based on scant evidence – 'hoping' that price moves in your direction is not a strategy. I do not like to trade by anticipating the direction of rate cuts or inflation data either. First, because it's very hard to predict; second, it's difficult to know what is already priced into the market; and third, because even if you're right, short-term volatility often results in price moves in both directions, stopping you out before eventually going in your favour. Ex-post, we can see that most trades taken were shorts, in line with our expectation of the S&P, but many longs were still taken intra-day.
I employed a scalping strategy to capitalize on intraday price swings rather than long-term trends for the reasons mentioned. Most trades were made on the 1-minute or 5-minute timeframes, often using higher time frames like the 1-hour or 4-hour charts to identify key levels where price had previously changed direction. Volume was also used

as a confluent factor in decision-making.

I did not make use of traditional technical analysis techniques such as triangle patterns, EMAs, Bollinger Bands, or other indicators. Instead, I focused solely on price action around basic support and resistance levels. Here is an example trade:

As this would be happening in real-time, we wouldn't have the benefit of hindsight as we do in providing this explanation, but the thought-process goes something like this: We can see that price is trending downward, therefore, we look for opportunities to short. Seeing that buyers were found (support) around $5910 (# and #2), and then lost this level (#3), we wish to join the trend.

We can't know exactly where sellers will come in, but we theorise that it will be around the level they came in before (highlighted pink). Why? 1. It takes a long time for large sellers to off-load stock - it's possible they still have inventory to sell. 2. Traders long from lower levels will want to take profit, and they will likely do this where sellers were encountered before. 3: Traders (like us) are looking for opportunities to join the downtrend - all these factors cause sell pressure. As we don't know exactly which price to trade at, we layer multiple limit-sell orders (#4), with stop-losses above, and target just above previous buy pressure. Then, we wait.

With the benefit of hindsight, we can see that price did indeed meet sellers at this level, and we would have profited from a 100-point move. Upon meeting this level again in the future (#5), sellers once again overwhelmed buyers, and the downtrend continued - an example, in trading parlance, of an area of support becoming resistance. Once price begins to move in the direction of our trade, we can move our stop-loss into the money. We do this because our risk evolves over time - once the trade is in profit, we stand to lose not only our original margin, but also our unrealized gains. By moving our stop, we not only lock in profit and make the trade 'risk-free,' but also manage our risk throughout the life of the trade.

Risk management was at the core of my scalping strategy. I used stop-loss orders on every trade, but rather than setting it a certain percentage away from entry, it was set beyond a key technical level – where previous liquidity had been found. As any given trade can be a losing trade, we aimed to risk only 1-3% of the account on any one trade, meaning that when stopped out, the maximum exposed was $10,000 - $30,000. As stop-losses were typically very close to entry price (as in our example), we were able to increase leverage and trade a large number of contracts - usually 2-5, but on occasion, as high as 50. I did not set a daily drawdown limit, but tried to remain level-headed, not increasing leverage to make up for prior losses. Journaling was also not used due to the fast-paced nature of the strategy; Up to 50 trades could be made on any given day, making it infeasible. Trades were almost always closed by the end of the trading day. If this was not the case, orders were set as 'Good Til' Cancelled' (GTC), to manage risk.

<u>Key lessons learned include</u>:

Risk management and discipline: Always set stop-loss and take-profit levels before entering a trade. Once in a position, it's very easy to get distracted by unrealized profit and loss.

Position size: Keep position size to a small percentage of your portfolio. The amount you stand to lose on any given trade should typically be no more than 1-3% of your account size ($10,000 - $30,000 on a $1m portfolio). As confidence in the trade idea increases, so should your position size.

Patience: Always use limit orders and let the trade come to you. Chasing trades using market orders is almost always the wrong thing to do and leads to many unnecessary small losses. In fact, if I had only taken the most obvious trades, PnL would've likely been higher - and stress lower.

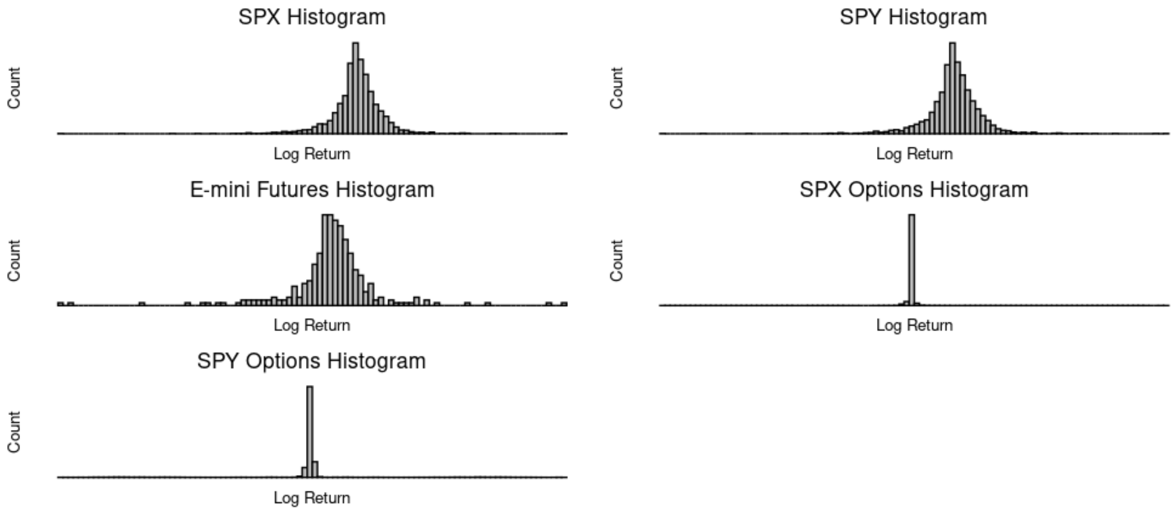
Focus on the downside: Focus on how much you can lose rather than how much you can win. Accept that you don't know which way the market will go, or for how big a move – have a pre-defined exit point.

Keep it simple: A simple strategy executed well is better than a complicated strategy executed poorly. Clean charts and simple setups allowed for clearer decision-making. Going forward, I would continue refining this simple, price-action-based approach while being even more selective with entries and controlling position size. Participating in the CME Trading Challenge with a scalping strategy using E-mini futures taught me invaluable lessons in discipline, adaptability, and simplicity. Executing 1,205 trades and growing the portfolio by over 72% reinforced that you don't need to predict macroeconomic events or overcomplicate trading with too many indicators. By sticking to price action, key levels, and tight risk management, I was able to thrive in a challenging and fast-moving trading environment - not to mention a massive losing period for the market as a whole.

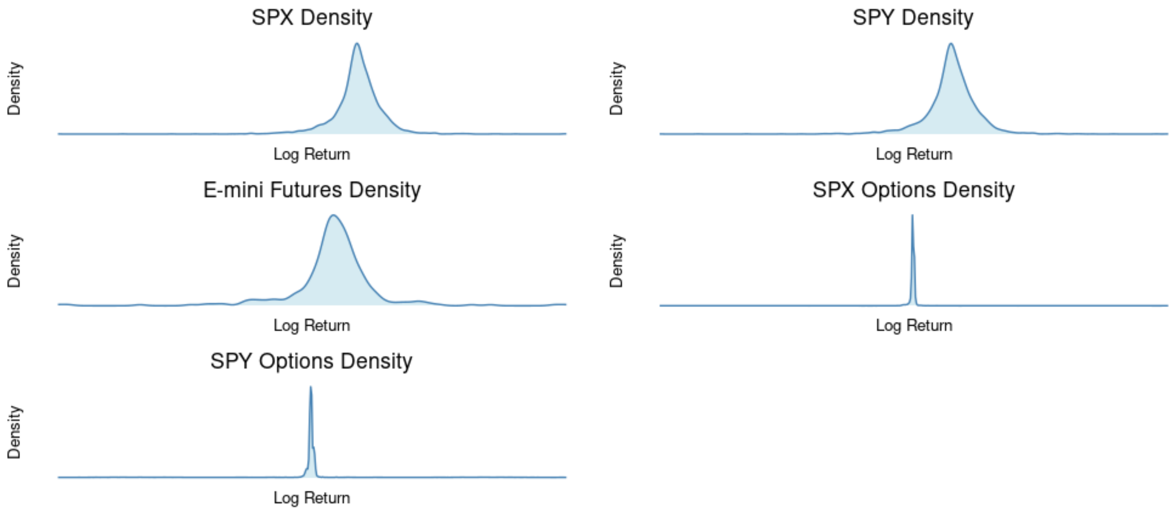
Appendix

1.1

1.1.A

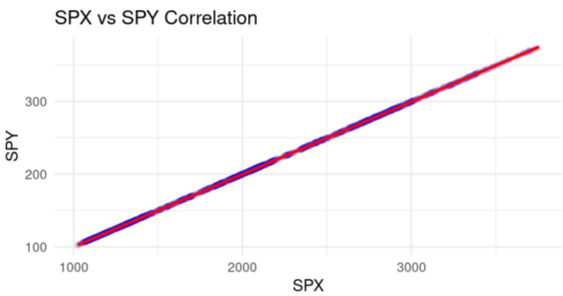


1.1.B



1.2

1.2.A



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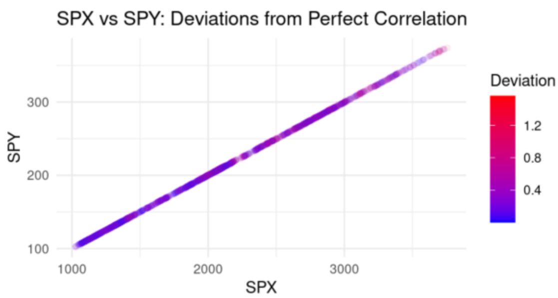
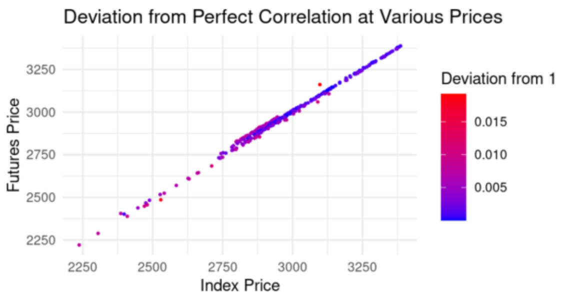


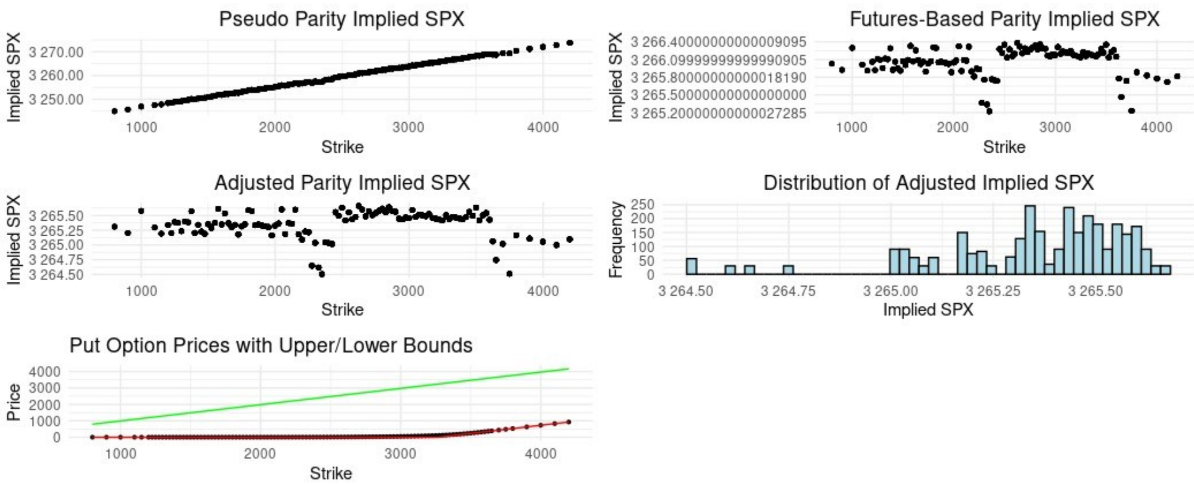
1.2.D

1.2.E

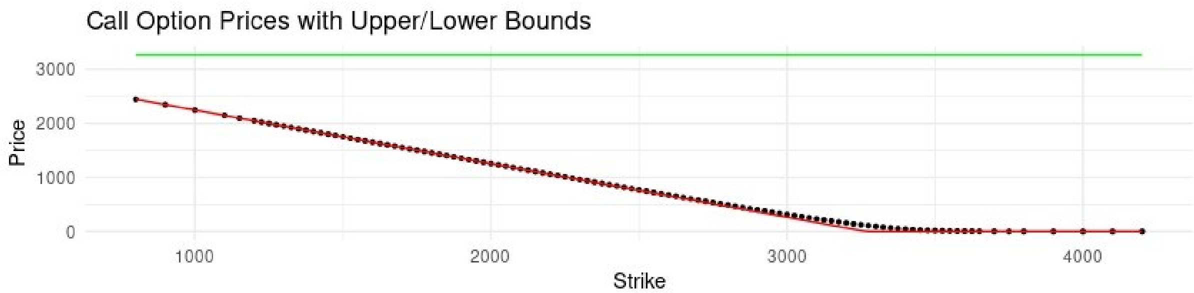


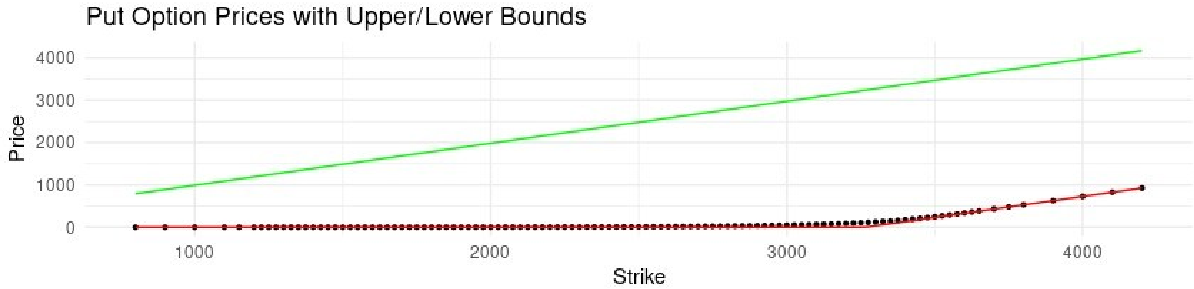
2

2.1



2.2





4

	Calm State				Crisis State			
	SPX	**WP**	**GWP**	**GBM**	**SPX**	**WP**	**GWP**	**GBM**
Mean	**3230.78**	2058.46	3630.15	3634.04	**3756.07**	3257.82	3783.77	3751.4
% off Mean		-36.2857	12.3614	12.482		-13.2652	0.7377	-0.1243
σ	**357.4528**	40.6382	501.4138	502.472	**319.22**	41.2164	1129.38	1117.33
Skewness	**0.1788**	0.046	0.4096	0.4056	**-0.6982**	0.0156	0.9012	0.8716
Kurtosis	**1.7059**	3.0047	3.2368	3.2612	**3.1617**	2.9944	4.4524	4.1555

5

8

8 D