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Blinded by science: The empirical case for quantum models in finance

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Abstract
The idea that markets are at equilibrium and price changes follow some version of a random walk or diffusion process is key to foundational results from quantitative finance including the Black-Scholes option-pricing model, and is related to other tenets of finance such as market efficiency and the no-arbitrage principle. However it is also inconsistent with the observed price behaviour of both assets and options. Quantum finance offers an alternative approach which captures the dynamic and probabilistic nature of financial transactions, and leads to different predictions of market behaviour. This paper summarises a range of empirical evidence which falsifies the classical equilibrium-based approach including the principles of no-arbitrage and market efficiency, and shows how contradictory data have long been downplayed or ignored in the classical literature. The aim of the paper is not to explain or justify the previously-published quantum model, but rather uses its predictions as a prompt to investigate data in a new way.

1. Introduction

Whether you can observe a thing or not depends on the theory which you use. It is the theory which decides what can be observed.

Albert Einstein (quoted in Salam, 1990).

Suppose the paradigm not only describes the subject matter of the field; suppose it also describes the field's appropriate methodology. In this case, observations that contradict the existing paradigm will be dismissed if they violate the prescribed methodology.

George A. Akerlof, 2020

In classical quantitative finance, prices are assumed to undergo some version of a random walk (or its continuum limit of a diffusion process) with a certain volatility, which may change with time. The idea goes back to the time of Bachelier (1900) who first used this approach to estimate the price of options on the Paris Bourse in his dissertation; and was rediscovered in the post-war era by economists including Paul Samuelson. It forms the basis of foundational theories from finance including the Black-Scholes model and the efficient market hypothesis, and it still shapes the way that economists and practitioners alike think about markets. Indeed, as seen below, the random walk assumption is so widely accepted that evidence to the contrary is often simply ignored.

While economists often speak of the "forces of supply and demand" the fact that these forces are assumed to be at equilibrium means that their nature is not explored. The quantum approach (Orrell, 2018; Orrell, Haven, and Hawkins, 2024) differs because it assumes that price can be modelled as a probabilistic dynamical system. The simplest kind of force to consider is a linear restoring force, as in a spring system. While we know that price does not follow deterministic oscillations, it turns out that the quantum version of a spring – the quantum harmonic oscillator – is a much better match.

This paper presents and compares a range of recent empirical evidence which falsifies the classical random walk approach, and supports the quantum model. The following sections consider some of the oldest and most basic questions in finance, namely the distribution of price changes; the response of asset price to large transactions; the relationship between volatility and price change; the pricing of options (which shapes economists' understanding of risk); and the nature of the implied volatility surface. In each case the classical theory is radically inconsistent with empirical findings, while the quantum model predicts them. Furthermore, the results directly contradict the principles of market efficiency and no-arbitrage which are central to the classical approach.

Before proceeding, we should note that the quantum model does not satisfy the "need to escape from imaginary worlds" (for one thing, it involves imaginary numbers) or counter the problem of "the uncontrolled use of mathematics" identified by protesting economics students in 2000 (Morgan, 2022). However, it does offer a coherent alternative to the neoclassical approach which allows one to see empirical evidence in a new way. Also, some readers drawing analogies with physics may associate quantum models with "spooky" or "magical" phenomena such as interference and entanglement, so will expect empirical evidence to come in that form. We return to this topic in the final section, but note that the test of a model is not its ability to surprise or confound, like a kind of magic trick, but rather its ability to understand and predict a system; and by this standard, as seen below, it is the classical approach which lacks empirical support.

2. The market bell

Quantum finance is a developing area which encompasses a range of techniques, but this paper will concentrate on the quantum oscillator model described in Orrell (2024a). To summarise briefly, the model represents the probability of a transaction between a buyer and a seller by a complex-valued wave function which rotates around the imaginary axis. The oscillator has an integer energy level which corresponds to the number of representative transactions in a time period. In its ground state, so the case with no transactions, the price uncertainty equates to the bid/ask spread, which gives a base level of volatility. By assuming that transactions across the bid/ask spread boost the energy level of the oscillator, the energy level should follow a Poisson distribution with an average of around $1/4$ (although this parameter can be adjusted).

Rather than treating price as being at equilibrium, the quantum model therefore sees transactions as caused by fluctuating imbalances between buyers and sellers, leading to a state which might be pictured as a kind of constant vibration (the leading three energy eigenvalues of the oscillator have frequency ratios of 1, 3 and 5, so the "tone" produced is a major chord).[1] This leads to a number of

[1] For example the following notes produce a major C chord: C1 (frequency 32.703), G2 (97.999), and E3 (164.81), so the frequency ratios are 1, 2.996636, and 5.039599, or about 1, 3, 5.

predictions about price behaviour, which have been presented in earlier form elsewhere and are summarised and refined here.

The first prediction concerns the correct distribution for log returns, which the classical model treats as Gaussian. Of course, the fact that log returns are not perfectly Gaussian is a well-known property of markets (Mandelbrot and Hudson, 2004; Wilmott, 2010: 219), and defenders of the classical model will point out that the model still serves as a reasonable approximation for most situations. The quantum model however predicts that, as a result of variable energy levels, log returns should follow a Poisson-weighted sum of Gaussians, of the sort shown in Figure 1 of Orrell (2024a). As seen later this quantum model allows us to make specific predictions about option pricing and implied volatility.

Another prediction relates to the question of market impact. A good way to understand the dynamics of a system, in physics, engineering, biology, or even economics, is to test how it responds to perturbations, such as in this case a large order. According to Kyle and Obizhaeva (2018) "Understanding market impact is one of the most puzzling and difficult issues in finance … theory suggests a market impact function has a linear functional form, with price impact proportional to the number of shares traded, while empirical evidence suggests a square root model, with marginal price impact diminishing as the number of shares traded increases." Attempts have therefore been made to develop models which match this observed behaviour; for example, Tóth et al. (2011) present a square-root model in which price change varies with the term $\sqrt{Q/V}$ where Q is the size of the excess order, and V is the average volume per day.

The square-root law also makes sense in the quantum picture, where the energy gain due to imbalance is countered by a shift in price, with the added benefit that the quantum model gives an estimate of unity for the multiplicative constant (Orrell, 2024a). However, a related question, which turns out to be key to broader topics such as option pricing, is what effect the excess order has on the volatility. If you hit a bell, you displace it but you also create a vibration, which makes a noise. So, when the market is struck by a large order, how loudly does it ring?

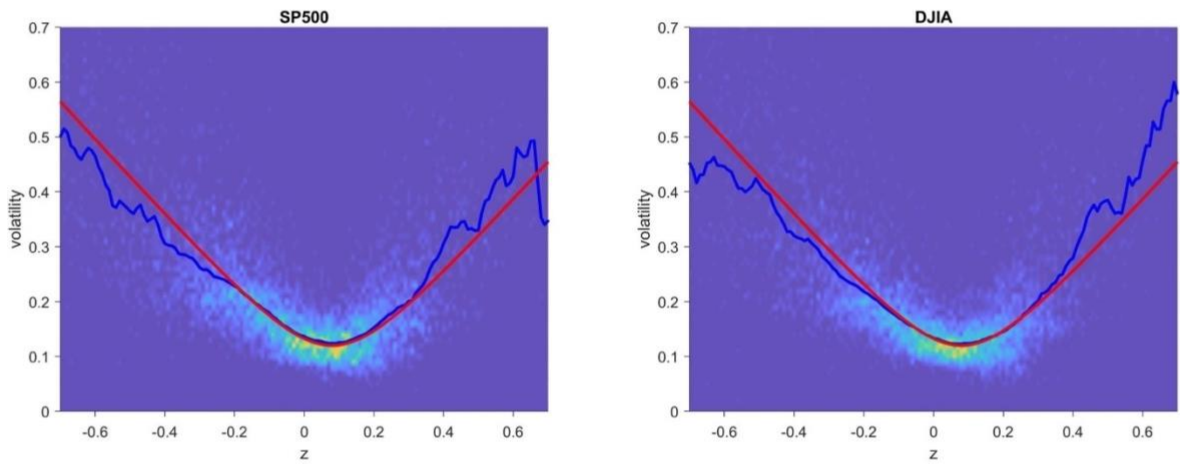
According to classical random-walk theory, the expected price change over a period *T* scales with the square-root of time, so volatility is assumed to have dimensions of inverse square-root of time (Pohl et al., 2017). The variance due to impact should therefore scale with the length of the period *T* over which the excess order occurs (Lillo, 2023). Empirical evidence is provided by (Bucci et al., 2019) which makes the same assumption, and demonstrates the model's prediction by plotting variance as a function of the excess order size. In the paper, the plot is made using log-log axes which are hard to interpret, however an obvious feature is that lines which are supposed to be parallel actually intersect; and a reanalysis of the data shows that a much better match is obtained if the variance depends on the inverse of the order time *T* as in Equation 1 (Orrell, 2024a). As with bells, a short, sharp hit (greater imbalance) creates more noise than a slower one.

A related prediction of the quantum model is that price change and volatility over a period are related by the simple equation

$$\sigma_z^2 = \sigma_0^2 + \frac{x^2}{2T} = \sigma_0^2 + \frac{z^2}{2} \qquad (1)$$

where $z = x/\sqrt{T}$ and x is log price change over a period T adjusted for average drift (Orrell, 2024a). The reason is that, as mentioned above, the quantum model assumes, not only that markets are not at equilibrium, but that transactions occur exactly because of market imbalances (where the oscillator is not in its ground state). In other words, markets are always being impacted. Equation 1 violates the classical assumption that volatility can be treated as constant, but is in good agreement with a range of empirical data including the S&P 500 and DJIA indices, as seen in Figure 1. (Note that this is an equation of actual volatility as a function of price change, not implied volatility as a function of strike price, which as discussed below has been more widely treated in the literature.)

Figure 1.
Heatmaps show volatility as a function of $z = x/\sqrt{T}$ where x is log price change over time periods T of 2 to 100 days (measured in years). Blue line is smoothed average volatility, red line is Equation 1 with offset to account for drift (so the minimum is slightly to the right of $z = 0$). Panels are for the S&P 500 1992-2023, and Dow Jones Industrial Average 1992-2023.



3. Option pricing

While the use of quantum probability changes how we model market behaviour, at a more fundamental level it also affects what constitutes an acceptable mathematical proof. In particular, a core tenet of classical finance is the no-arbitrage principle, which amounts to the idea that one cannot “make money out of nothing” by clever trading in the markets. As (Fontana, 2014) summarises, “Since the existence of such a possibility is both unrealistic and, loosely speaking, conflicts with the existence of an economic equilibrium, any mathematical model for a realistic financial market is required to satisfy a suitable no-arbitrage condition, in the absence of which one cannot draw meaningful conclusions on asset prices and investors’ behavior.”

However, hedge funds which exploit disequilibrium to extract value from financial markets might have a different perspective on what is realistic, or constitutes a meaningful conclusion (Wilmott, 2022); and the no-arbitrage principle only makes sense if transaction costs, and in particular the bid-ask spread between the seller’s ask price and the buyer’s bid price, are assumed to be zero. In the quantum model (or in real markets; see Wilmott, 2009) such arguments do not apply, because volatility is linked to the bid/ask spread. In the ground state, which corresponds to zero transactions, the base volatility is set by the half-spread, and reflects an irreducible level of uncertainty. Assuming that transaction costs are zero is therefore equivalent to saying that the volatility is also zero, which isn’t useful if the aim is to make a prediction that involves volatility.

One example of arbitrage is that of the market maker, who buys stocks at the lower bid price, and sells them at the higher ask price. The arbitrage can be thought of as a fee for providing liquidity to the markets. However the quantum argument is not that somehow arbitrage is easy, but only that the existence of the bid/ask spread means that transaction fees cannot be assumed to be zero.

These issues come to a head in the Black-Scholes option-pricing model (Black and Scholes, 1973). In their 1973 paper, the authors assumed that price changes are lognormal, and used a no-arbitrage/efficient-market argument to prove that the option price does not depend on the growth rate of the asset, but only on the risk-free rate r. The formula is therefore simply the expected payout from a call option whose underlying stock follows a lognormal price distribution with a drift equal to the risk-free rate. In fact, the formula was otherwise identical to an earlier result from Boness (1964), which featured a subjective estimate of a growth rate μ instead of the risk-free rate (Gatarek, 2023).

In a 1990 book Robert Merton wrote that “virtually on the day it was published [the model] brought the field to closure on the subjects of option and corporate-liability pricing,” while Paul Samuelson added in a forward: “one of our most elegant and complex sectors of economic analysis – the modern theory of finance – is confirmed daily by millions of statistical observations” (Merton, 1990). Again though, it turns out that the formula performs better in theory than in practice, according to four criteria.

Firstly, the model assumes that price changes follow a lognormal distribution. However it is again easily checked that the actual distribution has a sharper peak and fatter tails than expected.

Secondly: the main conclusion of the Black-Scholes model, which distinguishes it from the Boness model, is that to capture the effect of growth, only the risk-free rate matters. This follows from a “dynamic hedging” no-arbitrage/efficient-market argument where holdings of options and the underlying stock are constantly rebalanced to create a risk-free portfolio. As discussed earlier, such a process is impossible in practice because of things like transaction costs. And a little reflection (or data analysis) will show that if prices are tending to go up, then this will affect the expected payout of options. Since the S&P 500 typically sees an annual gain which far exceeds the risk-free rate, it follows that call options will have performed better than put options. Since the purpose of an option pricing formula is to predict the prices which match the expected payouts, the earlier Boness model is in this respect more realistic.

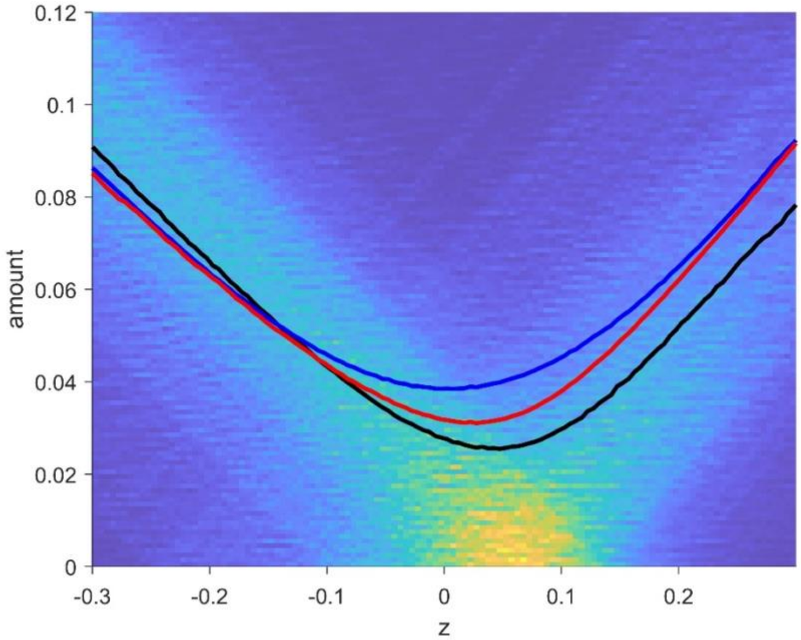
Thirdly, the Black-Scholes model, like the Boness model, assumes that volatility can be treated as a constant, and in particular is independent of strike and expiration. While this can work as a first-order approximation, as seen in the next section it leads to major problems in determining the properties of the implied volatility.

Of course, defenders of the theory will argue that such effects are well-understood and mostly come out in the wash. Again though, since the purpose of the formula is to predict the price which will match the expected payouts, a fourth and most basic test is to compare those prices with the actual payouts for historical data. The results are shown in Figure 2 for historical S&P 500 price data, with the VIX index as an estimate for implied volatility (for a discussion see Orrell and Richards, 2023). The Black-Scholes/VIX framework (blue line) gives systematic errors of up to about 40 percent when compared to actual payouts (black line). The background is a heatmap of actual straddle payouts over the period, representing over 4 million data points.

In practice, traders will adjust the volatility number, resulting in the implied volatility smile discussed further below, where at-the-money options with strike prices close to the current price tend to be assigned a lower implied volatility than options with more extreme strikes. The effect of this is to reduce the error by about half (red line), but it is still very significant, which is unsurprising given the influence of the dominant option-pricing model. This pricing error of course has not gone undetected;

researchers for example have noted that at-the-money straddle options consistently lose money. However rather than attribute this to a flaw in the model, it is rationalised as a "volatility risk premium" since straddles protect against volatility (Coval and Shumway, 2001; Goltz and Lai, 2009). As mentioned, one of the Black-Scholes assumptions was that markets are efficient, so price everything correctly and absorb new information instantaneously (Fama, 1965). The fact that the model has been helping to consistently misprice options for half a century therefore directly refutes its own assumption that markets are efficient.

Figure 2.
Plot of average price for 1-month straddle options versus log moneyness, for S&P 500 data over the years 2004 to 2020. The Black-Scholes model (blue line) systematically overprices options compared to the average payouts (black), while actual price paid splits the difference (red). The background is a heatmap of option payouts.



4. Implied volatility

Now, critics have been pointing out the drawbacks of the Black-Scholes model since the time it was invented – it is not news for example that price changes are not perfectly lognormal – but it is generally believed that the approach is "good enough" for its purposes, and the method has the advantage of simplicity. While one can add more refinements, just as ancient astronomers piled on epicycles to their geocentric models of the cosmos, the result will be a more complicated model with extra parameters that need to be set. And in any case, the results can be adjusted by choosing an appropriate implied volatility.

However, this flexibility is not a strength, because it means that the model can never be falsified. As Popper (1959) wrote: "In so far as a scientific statement speaks about reality, it must be falsifiable: and in so far as it is not falsifiable, it does not speak about reality." While it is trivially true that the model can be tuned to fit the data, the same could be said of just about any plausible model; and this simply shifts the burden of prediction from the model itself, to the choice of parameters. In this case, as (Derman and Miller, 2016: 5) observe, "The modeling of the volatility smile is likely one of the largest sources of model risk within finance" which is why much attention in recent decades has focused on this topic (Horvath, 2023).

Because the classical model assumes that volatility is independent of strike, the implied volatility smile appears from a classical perspective to be a "logical inconsistency" (Simons, 1997). It is interesting then that attempts to model the implied volatility using classical logic lead to perhaps the most graphic illustration of its departure from empirical reality.

One example, discussed in Orrell (2024b), is the calculation of the VIX volatility index (Cboe, 2019). The VIX algorithm assumes that volatility is described by a single number (its goal is to find it), which is the main assumption of the Black-Scholes model; that the applicable growth rate is the risk-free rate, which is the main conclusion of the Black-Scholes model; and the principle of no-arbitrage (Carr and Wu, 2006), which is central to classical finance. Since none of these assumptions apply, the results of the algorithm are confusing at best. The historical average of the VIX index is about a third higher than the average realized volatility (Ahmad and Wilmott, 2005), which is the number relevant for option pricing. Also the fact that put options attract higher prices when markets are perceived to be falling means that the VIX algorithm, which tends to overweight these, is measuring not just perceived future volatility, but also perceived future price changes, which explains why the index is negatively correlated with price change (Bauer, 2022).

More generally, economists model implied volatility by constructing three-dimensional surfaces which specify its value as a function of log-moneyness x and expiration time T. A foundational result from Lee (2004) claims that "the large-strike tail of the Black-Scholes implied volatility skew is bounded by the square root of 2|*x*|/*T*." A consequence of the result is that the implied volatility in the tails cannot grow faster than $|x|^{1/2}$. According to (Raval and Jacquier, 2023) the formula "serves not only to infer directly observed information about the implied volatility smile into constraints on model parameters but also to provide arbitrage-free solutions to the extrapolation problem." For example (Lee, 2004) recommended that for extrapolating the volatility skew with splines, the formula "raises warnings against spline functions that grow faster than $|x|^{1/2}$, and against those that grow slower than $|x|^{1/2}$" which seems to limit the choices.

As an example, one popular approach is the stochastic volatility inspired (SVI) model given by

$$\sigma^{SVI} = \sqrt{\left|a + b\left(\rho(x-m) + \sqrt{(x-m)^2 + \sigma^2}\right)\right|}$$

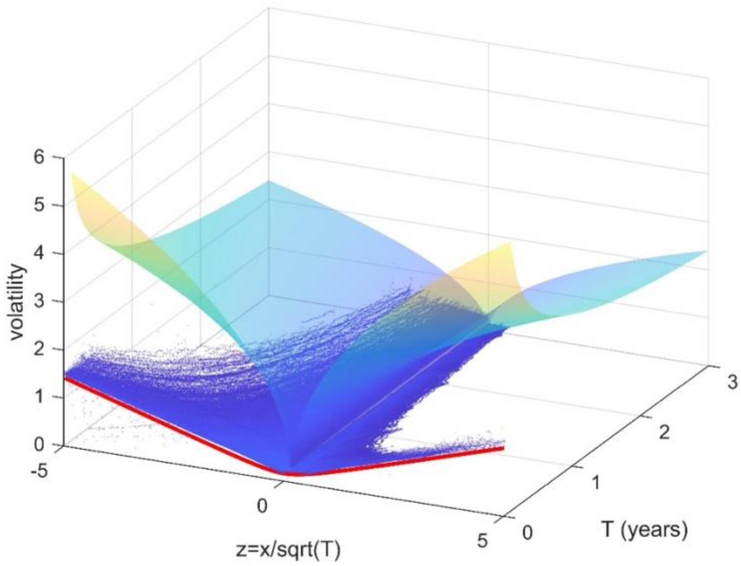
which requires five parameters that must be calibrated for each expiry time. For large $|x|$ this formula scales with $|x|^{1/2}$ and therefore automatically satisfies Lee's formulas (Gatheral, 2006).

While it is beyond the scope of this paper to discuss the full array of implied volatility models, according to (Gatheral, 2006: 100) "the general shape of the volatility surface doesn't depend very much on the specific choice of model" especially since such models are usually designed to respect the Lee (2004) bounds. But while Lee (2004) stresses that "our formula is distinguished by its full *model-independent* generality" (his italics) it is based on the classical equilibrium-based, random walk approach. As with the Black-Scholes model, the proof relies on a no-arbitrage argument, and assumes for example that there is a parameter σ which corresponds to the volatility.

Again though the test of a model is not whether it is consistent with abstract theory or idealized principles, but whether it makes accurate predictions about the system's behaviour. Implied volatility is complicated by a number of behavioural and other effects (Derman and Miller, 2016; Orrell, 2021), so the situation actually becomes clearer when we stand back to take a bird's eye of volatility for a large range of strikes and expirations as in Figure 3, which shows implied volatility as a function of T and $z = x/\sqrt{T}$. The data, shown by the blue points, is derived from SPX options during the period 2004-2020 (Orrell, 2024b). The option prices are averaged over each strike and expiration (from five days to three years), and the implied volatility is then computed assuming a constant risk-free rate for each year (this has only a small effect on the results). The classical bound (shown by the upper smooth curve) is too high to be useful, scales differently with both T and z, and generally bears little resemblance to actual data. A consequence is that models such as SVI which are designed to scale in the same way fail to capture the behaviour of implied volatility in the wings (Orrell, 2024c).

The red line is the quantum implied volatility model (Orrell, 2024c), which is derived by assuming that price change follows the associated non-lognormal distribution. The implied volatility can then be approximated as the volatility which gives the correct option price for that distribution. The fact that, over a large range of strikes and expirations, the agreement with observed data is good suggests that investors expect the market to have the same non-lognormal characteristics. In other words, while from a classical perspective the implied volatility curve seems to be a puzzling and illogical anomaly, it is best viewed as a numerical anachronism which results from a normal model being used to model a non-normal system. Instead of being a sign that market participants are illogical, it is a marker of model error.

Figure 3.
Plot of implied volatilities (dark blue points) from SPX options 2004-2020, plotted as a function of $\boldsymbol{T}$ and $\boldsymbol{z}$. Smooth surface is the upper bound from Lee (2004). Red line is the quantum model for implied volatility, which is constant along the $\boldsymbol{T}$ axis when plotted in this way.



5. Conclusions

To summarise, key results from classical finance – which ultimately derive from core principles including no-arbitrage and efficient markets – are based on the idea that price changes follow a lognormal distribution with a drift equal to the risk-free rate. Empirical evidence, on the other hand, shows that price change follows a distribution with sharper peaks and fatter tails, and a drift equal to the growth rate. While the Black-Scholes model gives correct results (by definition) if you input the correct implied volatility for the particular strike and expiration time, the classical approach breaks down completely when it is used to calculate this number (as with the VIX index) or predict its properties (such as its scaling behaviour). Better results can be obtained if you assume that price change follows the quantum distribution, and use that to determine a strike-dependent implied volatility. Or more simply, since the concept of implied volatility refers to a lognormal framework: just generate the corresponding price distribution, including an estimated growth term, and calculate the option price numerically from the expected payout.

The reason that the Black-Scholes model took its place in the financial firmament, while the Boness model is usually mentioned only in books about the field's history (Gatarek, 2023), is because by replacing a subjective growth estimate with an objective risk-free rate, it appeared to put option pricing onto a rational, objective basis, with only one unknown parameter remaining, namely the volatility (Orrell, 2023). But that is a marketing test, not a scientific one (Wilmott, 2022). And the apparent simplicity was won only by exporting the complexity to the calculation of the implied volatility. The net result is that the classical option-pricing model – which helps underpin the quadrillion dollars worth of derivatives that hang over the world economy (Wilmott and Orrell, 2017) – systematically misprices risk.

In general, classical models typically have little or no predictive power because they rely on made-up parameters with no financial interpretation. With one extra fitting parameter, intersecting lines can be made parallel. With five parameters, financial engineers can fit the implied volatility curve, at least for a single expiration and some strikes; however, the formula still does not work in the wings. For comparison, Von Neumann once said "With four parameters I can fit an elephant, and with five I can make him wiggle his trunk" (Dyson, 2004). Rather than coerce a flawed model into giving sensible answers, a better approach is to start with the quantum model, which (being based on the quantum version of a spring) in terms of parameters is about as simple as a useful model can get.

An inescapable conclusion from the results above is that economists appear to have been turning a blind eye to data which contradicts the classical model. While other areas such as biology and psychology have experienced a replication crisis, where published results cannot be reproduced (Baker, 2016), the problem here seems worse, because observations which do not fit the data are simply ignored. A plot of intersecting lines for the variance due to price impact is taken as proof that the lines are parallel. The Black-Scholes model is called "the most successful theory not only in finance, but in all of economics" as measured by its "ability to explain the empirical data" (Ross, 1987); but claims that the formula is confirmed daily by "millions of statistical observations" do not hold up when we test it using millions of statistical observations. The implied volatility smile is treated as a puzzling anomaly, even though actual volatility shows a similar (but more accentuated) shape when plotted against price change. Figures 2 and 3 clearly violate the efficient market hypothesis (since option prices do not reflect payouts) and the no-arbitrage principle (since the Black-Scholes model and the Lee model do not match observed data) on a truly industrial scale, but the necessary data to make the comparison has long been publicly available. In short, the classical model seems to have been immune to any empirical evidence which contradicts it, due to what might be called a form of model blindness, where the model takes priority over observed reality.

As (Derman and Miller, 2016: 3) note, the Black-Scholes model "sounds so rational, and has such a strong grip on everyone's imagination, that even people who don't believe in its assumptions nevertheless use it to quote prices at which they are willing to trade." More to the point, they also consistently and in a variety of contexts ignore evidence which doesn't fit the story.[2] A historical analogy is provided by supernovas, those massive stellar explosions which release a burst of radiation lasting months or even years. The first observations of such events by Western astronomers were in 1572 (recorded by the astronomer/alchemist Tycho Brahe) and then 1604 (recorded by his associate Johannes Kepler). However, Asian astronomers had known about them for centuries. The reason it took so long for the West to catch on was because astronomers there were blinded by Aristotelian science, which said that the planets rotated around the earth in spheres made of ether, and the heavens were immutable. Brahe also tracked a comet and showed that it would have smashed through those crystalline spheres, had they existed. As Abraham (2005) wrote, "We have to conclude that the astronomers of medieval Europe were effectively blinded by their faith in Aristotelian dogma."

Since its invention, classical quantitative finance has been built on the crystalline spheres of efficiency, rationality, and equilibrium, which seem similarly robust to contradictory evidence. Elaborate mathematical proofs for theories such as Black-Scholes are constructed from the principles of market efficiency and no-arbitrage, despite the fact that arbitrage is the main business model of much of the financial sector. Of course, mathematical models do not just conceal, they also act as prompts to investigate. The experiments described in this paper, including the reanalysis of price impact data, the relationship between volatility and price change, the test of theoretical and observed option prices against payouts, and the nature of the implied volatility curve, were all motivated by predictions of the simple quantum model. One can always argue that such effects could in principle be modelled using a sufficiently complicated classical model (just as a quantum computer can be emulated with a classical computer), but perhaps the best empirical defence of the quantum approach is that they weren't.

Mathematical models are vital to the proper functioning of markets because they are used to put a price on assets, options, and risk in general. As in other fields such as engineering, modellers therefore have an ethical responsibility to ensure that their models are giving accurate guidance, especially given the role that models have played in previous crises (Wilmott and Orrell, 2017). Instead, economists often seem as obsessed with their elegant equations and normal distributions ("normal" is from the Latin for "square") as early astronomers were with circles and spheres. Writing in the aftermath of the 2007/8 financial crisis, Bouchaud (2008) called on economists "to focus on data, which should always supersede perfect equations and aesthetic axioms." Wilmott (2010: 377) warned, "Being blinded by mathematical science and consequently believing your models is all too common in quantitative finance." Akerlof (2020) observed that the emphasis in economics on "hard" mathematics meant that "observations that contradict the existing paradigm will be dismissed if they violate the prescribed methodology." But maybe part of the problem is the type of mathematics. It is past time for economists to open their eyes to the possibility that markets and the economy are not as normal or square-like as their classical equilibrium-based models suggest.

References

Abraham R (2005) The broken chain. http://www.ralph-abraham.org/articles/MS%23117.Kepler/kepler02.pdf (accessed 14 November 2023).

Ahmad R, Wilmott P (2005) Which free lunch would you like today, sir?: Delta hedging, volatility arbitrage and optimal portfolios. *Wilmott* 2005 (November): 64-79.

Akerlof GA (2020) Sins of Omission and the Practice of Economics. *Journal of Economic Literature* 58(2), 405–418.

[2] An amusing example was provided by comments on an earlier version of this article (Orrell, 2024d).

Bachelier L (1900) Théorie de la spéculation. *Annales Scientifiques de l'École Normale Supérieure* 3 (17): 21–86.

Baker M (2016) 1,500 scientists lift the lid on reproducibility. *Nature* 533: 452–454.

Bauer S (2022) Inside Volatility Trading: Breaking Down the VIX Index and its Correlation to the S&P 500 Index. https://www.cboe.com/insights/posts/inside-volatility-trading-breaking-down-the-vix-index-and-its-correlation-to-the-s-p-500-index/

Black F, Scholes M (1973) The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81(3): 637-654.

Boness A J (1964) Elements of a Theory of Stock-Option Value. *Journal of Political Economy* 72(2):163–175.

Bouchaud JP (2008) Economics needs a scientific revolution. *Nature* 455: 1181.

Bucci F, Mastromatteo I, Benzaquen M, Bouchaud JP (2019) Impact is not just volatility. *Quantitative Finance* 19(11):1763-6.

Carr P and Wu L (2006) A tale of two indices. *Journal of Derivatives*, *13*(3): 13-29.

Cboe (2019) Cboe Volatility Index.

Coval JD, Shumway T (2001) Expected option returns. *The Journal of Finance* 56(3):983-1009.

Derman E, Miller MB (2016) *The volatility smile*. Hoboken, NJ: John Wiley & Sons.

Dyson F (2004). A meeting with Enrico Fermi. *Nature* 427 (6972).

Fama EF (1965) *Random walks in stock-market prices.* Chicago: Graduate School of Business, University of Chicago.

Fontana C (2014). Weak and strong no-arbitrage conditions for continuous financial markets. *International Journal of Theoretical and Applied Finance*. 18: 1550005.

Gatarek D (2023) The principle of two models: The cases of Black-Scholes formula for interest rates and of Gaussian copula for credit. *Wilmott* 2023(125): 72-76.

Gatheral J (2006) *The volatility surface: A practitioner's guide*. Wiley.

Goltz F and Lai WN (2009) Empirical properties of straddle returns. *The Journal of Derivatives* 17(1), 38-48.

Horvath BN (2023) Golden jubilee for an iconic financial formula. *Nature* 618: 243-245.

Kyle AS and Obizhaeva AA (2020) The Market Impact Puzzle. Working Papers w0270, New Economic School (NES).

Lee RW (2004). The moment formula for implied volatility at extreme strikes. *Mathematical Finance* 14, 469–480.

Lillo F (2023) Order flow and price formation. In: Capponi A, Lehalle CA, editors. *Machine Learning and Data Sciences for Financial Markets: A Guide to Contemporary Practices*. Cambridge University Press, pg 122.

Mandelbrot BB, Hudson RL (2004) *The (Mis)behaviour of Markets: A Fractal View of Risk, Ruin and Reward*. London: Profile.

Merton RC (1990). *Continuous-Time Finance*. Cambridge, MA: Basil Blackwell.

Morgan J (2022) Postscript: RWER is for everyone and no one. *Real-world economics review* (100): 264-267.

Orrell D (2018) Quantum Economics. *Economic Thought* 7(2): 63-81.

Orrell D (2021) A quantum walk model of financial options. *Wilmott* 2021(112): 62-69.

Orrell D (2022) *Quantum Economics and Finance: An Applied Mathematics Introduction*. Third edition. New York: Panda Ohana.

Orrell D (2023) The Black-Scholes Magic Trick, Explained! *Wilmott* 2023(126): 90–93. doi={10.54946/wilm.11153}

Orrell D (2024a) A Quantum Oscillator Model of Stock Markets. *Quantum Economics and Finance* 1 (in press).

Orrell D (2024b) Quantum Uncertainty and the Black-Scholes Formula. *Quantum Economics and Finance* 1 (in press).

Orrell D (2024c) A quantum model of implied volatility. *Wilmott* (in press).

Orrell D (2024d) Quantum economics – real or fake? https://futureofeverything.wordpress.com/2024/02/07/quantum-economics-real-or-fake/

Orrell D and Richards L (2023) Keep on smiling: Market imbalance, option pricing, and the volatility smile. *Wilmott* 2023(124): 58–64. doi={10.54946/wilm.11108}

Orrell D, Haven E, and Hawkins R (2024). What is quantum economics and finance? *Quantum Economics and Finance* 1 (in press).

Pohl M, Ristig A, Schachermayer W, Tangpi L (2017) The amazing power of dimensional analysis: Quantifying market impact. *Market Microstructure and Liquidity* 3(03n04):1850004.

Popper KR (1959) *The Logic of Scientific Discovery*. New York: Basic Books.

Raval V, Jacquier A (2023) The log-moment formula for implied volatility. *Mathematical Finance*.

Ross SA (1987) Finance. In *The New Palgrave Dictionary of Economics*, vol. 2, edited by J Eatwell, M Milgate and P Newman. London: Macmillan.

Salam A (1990) *Unification of Fundamental Forces*. Cambridge: Cambridge University Press.

Simons K (1997) Model error. *New England Economic Review* (Nov) 17-28.

Tóth B, Lemperiere Y, Deremble C, De-lataillade J, Kockelkoren J, Bouchaud J-P (2011) Anomalous price impact and the critical nature of liquidity in financial markets. *Physical Review X* 1(2): 21006.

Wilmott P (2009) Where quants go wrong: A dozen basic lessons in commonsense for quants and risk managers and the traders who rely on them. *Wilmott* 1 (1):1-22.

Wilmott P (2010) *Frequently Asked Questions in Quantitative Finance*. Chichester: Wiley.

Wilmott P (2022) How Good is Black–Scholes–Merton, Really? In: Options – 45 Years Since The Publication Of The Black-Scholes-Merton Model: The Gershon Fintech Center Conference 2022 Dec 21 (Vol. 6, p. 17). World Scientific.

Wilmott P and Orrell D (2017) *The Money Formula: Dodgy Finance, Pseudo Science, and How Mathematicians Took Over the Markets*. Chichester: Wiley.

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