Wyższa Szkoła Bankowa we Wrocławiu

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Trading strategies based on predicting prices of futures contracts

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INTRODUCTION

Derivative markets for commodities and currencies play a vital part in the modern-day international financial world by allowing market participants to manage their risk or engage in trading activities to generate or maximize profits. Futures contracts for high-value metals such as Gold are used extensively by organizations that Gold in their manufacturing processes and financial institutions to manage their risk due to the well-established inverse correlation between market volatility and the metal price.

Accurately predicting the price of Gold Futures, one of the world's most actively trading commodities, has always been important for academics and traders. The author reviews development of derivatives markets and trading strategies, and statistical techniques traditionally used in forecasting. Many well-known models such as Black-Scholes failed traders and markets during the financial crises of 2009, so the development and application of new approaches are critical for users of derivatives to have confidence in prices and settlement procedures.

Recent developments in machine learning algorithms gained wide adoption in some industries, but their applicability to derivatives trading has not been extensively covered in academic literature.

The author evaluates the performance of machine learning algorithms when trying to identify the formation of a new upward trend in the price of Gold Futures at the very beginning. The application of machine learning methodologies shows the scarcity of linear relationships between historical prices and new trend development. Black box models such as Neural Networks and specifically Autoencoders allow traders and analysts to classify observations in a way that can be used by entities engaged in trading of gold futures.

The first purpose of this project is to review one segment of the derivatives market - Futures Contracts and trading strategies used by different participants and modelling techniques involved in decision making. A good understanding of the way how derivative markets work and their settlement is processed is essential when deciding on potential trading strategies and modelling techniques.

The second purpose is to review forecasting techniques used to predict future prices of various financial instruments and identify those that can potentially be applied to Futures contracts as a basis of trading strategies. These forecasting approaches are well covered in academic literature but are not always used across many asset classes.

The primary purpose of the research part is to explore the suitability of Machine Learning Algorithms (MLAs) and State Space Time Series models for decision making in the proposed Gold Futures trading strategy. The topic of predictability of regime changes is not well covered in academic research as it is a very complex matter where traditional model efficiency metrics are not very applicable. This paper looks to add scientific value in predicting regime changes in time series and their application in the financial markets.

The proposed strategy relies on crossovers of 4-day and 9-day moving averages of daily Close prices for Buy signals. Historically about 30% of trades meet pre-defined minimum profit targets. The strategy may be profitable overall due to the average profit being approximately three times higher than the average loss, but trade signals are infrequent, and the exact probability of hitting a minimum profit target is unknown.

Some factors frequently mentioned in non-scientific literature for traders, such as pattern formations and resistance levels, are not easily quantifiable in terms of risk. Using historical variables to approximate them, the author believes that a 30% success rate can be improved to deliver a more profitable strategy with a better understanding of underlying risk.

Predictive potential of the data was improved by applying specific machine-learning methodologies. These methodologies aggregate information available at points of time when entering into a trade is considered.

Only employment of black-box models such as Neural Networks allows for predicting the probability of success with an accuracy of over 40%. The alternative Time-series approach yields an accuracy of over 70%; however, it cannot be directly compared to other methods due to its nature. The analysis demonstrates that additional historical price data has moderate predictive power for estimating the success of trades of Gold Futures with preset conditions.

List of Keywords:

Futures contracts, Derivative Instruments, Machine Learning, Neural Networks, Autoencoders, Bayesian Structured Time Series, State Space Models, Short-term Trend Forecasting, Futures Prices Forecasting.

1. THE ESSENCE AND APPLICATION OF FUTURES CONTRACTS

Some securities and instruments in the financial marketplace are considered fundamental, while others are considered derivative. For example, the stock and bonds issued by a corporation are regarded as fundamental securities and form the fundament of the financial system. Every corporation' must have stock, and stock ownership gives rights of ownership to the firm. Owning a bond issued by a firm gives the bondholder the first claim on the firm's cash flows (Kolb, 2000, p. 2).

In contrast with fundamental securities, such as stocks and bonds, there is an entirely distinct class of financial instruments called derivatives. In finance, a derivative is a financial instrument or security whose payoffs depend on a more primitive or fundamental good. A gold futures contract is a derivative instrument due to the value of the futures contract being dependent on the value of the Gold, which underlies the futures contract. The spot price of physical Gold is the key since the price of a gold futures contract is derived from the value of the underlying Gold. (Kolb, 2000, p. 2)

A financial derivative instrument can be defined as a financial instrument or security which payoffs are contingent upon the value of another financial instrument or security. For example, an option on a share of stock is contingent upon the value of the underlying share. Because the underlying asset for a stock option is a financial instrument, a stock option is regarded as a financial derivative. Similarly, a futures contract on a Treasury bond is a financial derivative because the value of the T-bond futures depends on the value of the underlying Treasury bond. (Kolb, 2000, p. 2)

Future is a derivative instrument comprising a contract concluded between the seller (or the buyer) and the stock exchange or clearinghouse, in which the seller (buyer) undertakes to sell (buy) a specific underlying instrument for a precisely defined price at a strictly specified date. The price at which the parties will conduct transactions in the future is called the future price, while the day on which the parties are required to carry out the transaction is the settlement date or the delivery date (Redhead, 1997).

It is also important to note the beginnings of such transactions to understand the underlying processes of futures contracts. The beginning of the history of derivatives dates back to the time of ancient Greece. According to historical sources, the well-known philosopher and mathematician Tales negotiated the right to use the machine for pressing olive oil for the following year. The actual demand for such devices was not formed until the spring harvest and depended on their size.

The first options market was created in the Netherlands in the 17th century when the country was in the middle of speculative madness over tulip bulbs. At the end of the 19th century, people were trying to establish the rules governing the derivatives market, and Russell Saga (referred to by some as the godfather of the options market) developed the concept of call-put parity the conversion at that time. However, until the end of the 1960s, the development of the derivatives market was slow enough that using the word "development" to some extent is an exaggeration. Trading in derivatives, the value of which was then a tremendous unknown to everyone, was based solely on theoretical considerations. This resulted in rapid changes in derivatives prices, high spreads between bids and offers, and above all, low liquidity. Against this background, commodity markets stood out, where most transactions were concluded for hedging purposes (Markham, 1987, p. 31).

In the finance sector, a futures contract, also called simply futures, is a type of forward contract that's been standardized as a legal agreement to purchase or sell an item at a previously determined price (forward price) of purchase and at a defined time in the future (delivery date). Futures contracts carry out transactions of assets such as commodities or instruments used in finances (Chew, 2008, p. 23).

All matters related to futures contracts are negotiated at special exchanges called futures exchanges that act as marketplaces for sellers and buyers. The latter is known as a long position holder and the former a short position holder. There is, however, a risk that both parties of the agreement may decide to terminate it or simply walk away if the negotiated prices are not favourable to them. Therefore, the parties can lodge a margin of the contract value with a neutral third party. For instance, in the gold futures trading, the margins are between two per cent and twenty per cent (Valdez, 2000, pp. 34-36).

As for its origins, the beginning of futures contracts can be traced back to 1972, when they were primarily used to negotiate agricultural commodities. Later on, they were mainly applied to transactions that concerned natural resources like oil. Over time, this type of contract has developed, and now we can come across such terms as currency futures, interest rate futures and stock market index futures, which play a significant role in the overall futures market (Chew, 2008, p. 26).

Initially, the primary purpose of futures contracts was to mitigate the risk associated with price and exchange rate movements by letting the parties fix prices or rate transactions, which were to be finalized at a later time in advance. It came in handy when parties expected payments in advance, which came in foreign currencies. In order to avoid unfavourable exchange rates, the given party can guard itself against such rates (Hull, 2000, p. 20).

The crucial moment in the development of derivative instruments was in 1973. At that time, two important events took place that significantly impacted the development of the derivatives market: a standard option valuation model was developed and introduced to stock exchange trading (Markham, 1987, p. 30). During the following years, the market of the first derivative instruments, such as futures contracts and standard options, rapidly expanded. This success resulted from several reasons. What is perhaps most important, the first models for determining the theoretical value of derivatives were developed - the breakthrough was the presentation in 1973 by Fischer Black and Myron Scholes of a model for the valuation of European standard options for shares of companies not paying dividends. Until this moment, no one really knew how much options are worth, which had a significant impact on the low liquidity of the market and high price volatility.

Over the next several years, the Black-Scholes model was extended to other base instruments: currencies (Garman-Kohlhagen and Grabbe models), futures (Black's model), dividend-paying shares (Merton's model). At the same time, work was undertaken to bring the model closer to reality by repealing its assumptions. They resulted in Thorpe models (abolished restrictions on short sales), Cox and Ross (introduced discontinuous changes in the underlying instrument prices), Jarrow and Rudd (they left the logarithmic-normal price distributions) and Merton (introduced a variable interest rate). Equally important, all the above-mentioned models directly impacted the practice of trading: financial institutions could manage their position in the derivatives market more effectively and consciously (Markham, 1987, p. 31).

The first and second oil market shocks significantly increased the uncertainty regarding the situation on commodity markets. On the other hand, changes in the global economy have led to the increased risk incurred by enterprises, banks and other financial institutions. The collapse of the Bretton Woods system in 1971 led to the release of exchange rates, and thus a significant increase in currency risk. Moreover, there was an increase in interest rate volatility on the deposit and bond market, which was influenced by such events as the change in the mid-seventies and eighties of intermediate goals in US monetary policy and the emergence of the eurodollar deposit market. All of the above events had a negative impact on capital markets, which was manifested, among others, in the increase in risk measured by the volatility of share prices.

Economic operators wishing to liquidate or at least reduce the risk incurred were forced to hedge their positions on the derivatives market. At the same time, the increase in the volatility of the prices of many assets created better opportunities to make speculative profits. Both of these factors contributed to the formation of the demand side (Markham, 1987, p. 33).

For derivatives to be able to achieve spectacular success, it was necessary to meet one more condition: to create a market where the supply side and the demand side could meet. As long as the trading took place exclusively on the OTC market, its value was small. The breakthrough took place with the introduction of derivative instruments to stock exchange trading in the early seventies. Trading in stock options began in the year of the Black-Scholes model announcement on the Chicago Board Option Exchange (CBOE) created by the Chicago Board of Trade (CBOT). In the early eighties, options for exchange rates, stock market indices and futures were introduced. Much earlier, as early as in 1972, trading in currency futures contracts at the International Monetary Market (IMM) was launched - the Chicago Mercantile Exchange (CME) branch (Markham, 1987, p. 35).

The price that investors had to pay for using the stock exchange options was their standardization. The limitation of the freedom to choose option parameters was compensated by higher liquidity on the exchange market and thus lower costs of opening and closing the market position.

Seemingly in the background, the future development of the exotic instruments market was underway. As in the case of standard options, the first of these was the development of models for determining the theoretical value of some exotic options. In 1973, Merton presented a model for the valuation of barrier purchase options with a low barrier, on which the valuation of other barrier options was also based. At the end of the 70's models of swap option valuation (Margrabe model), complex options (Geske model), and reverse options (Goldman, Sosina and Gatto models) were developed. The eighties brought, among others, Stulz (option pricing for maximum or minimum two base instruments) and Ingersoll (first Asian option pricing model) models. Furthermore, this time the decisive factor was the fact that the financial institutions adopted the theoretician's thesis to the requirements of reality.

The second factor, which impacted the emergence of the exotic options market, was the desire to offer new banking products to customers, on which a higher margin could be realized. Thanks to the introduction of standard options and futures contracts to stock exchange trading, the interest of investors in derivative instruments began to proliferate, spreading narrowed, which limited the profits of market makers, which were primarily financial institutions. The introduction of new instruments to the market, in addition to a much lower standardization, allowed for achieving above-average profits (of course, provided that the demand side in this market existed) (Duchock, 1990, p. 106). Not without significance was the fact that financial institutions began to have more effective and fast IT and telecommunications systems, allowing for ongoing monitoring of the position and analyzing a huge amount of data.

Formation of the demand side on the exotic instruments market took a bit longer. This was due to several reasons: initially available derivative instruments (standard options and futures contracts) were enough to hedge and speculate. In more complex cases, option strategies or other combinations of several derivatives were used. At the same time, market participants perceived exotic options as very complicated, and the knowledge of the principles of their operation was small (Van Blokland, 1995, p. 155).

However, over time, investors' knowledge slowly, albeit systematically, increased. Potential buyers began to see the benefits of using exotic options, two of which were decisive for market development: lower price and greater flexibility. Prices of exotic instruments were lower than the costs of linear combinations of standard options generating similar positions on the underlying market. In addition, it was not possible in each situation to create a position that suited the needs of investors using only standard instruments. Exotic options offered the buyer much more flexibility and allowed for a better fit to individual needs. Together with the stable demand for new products, the next stage of derivative instruments development is beginning - the rapid development of the non-standard instruments market.

Unlike in the case of standard instruments, the trading venue for exotic options was the OTC market. As was already mentioned, the attempt to standardize basic derivative instruments undertaken by the world's major futures exchanges proved to be so effective that currently, most trading in these instruments falls on regulated markets. In the case of exotic options, this situation did not repeat itself. The reason for that was the complex nature of these instruments, making it more difficult to impose on the standardization framework. Secondly, the trading of exotic options on the OTC market has not yet reached such a size that, considering the variety of available instruments, transferring its part to the stock market was feasible. To date, the most standard exotic options have been introduced to stock exchange trading, e.g. barrier options or lookback options (Redhead, 1997, p. 89).

The period of rapid development of the exotic options market lasted from the end of the eighties until the second half of the nineties. Over the past few years, we have witnessed a slight slowdown in growth. The first symptoms of this process occurred in the mid-nineties when many recognized financial institutions went bankrupt due to operations carried out on the derivatives market. Of the many examples, it is worth mentioning the most spectacular ones. In 1992, the Japanese company Showa Shell Sekiyu lost over USD 1.5 billion on USD / JPY futures. A year later, the German Mettalgesellschaft AG beat the infamous record of losses with 1.8 billion dollars. In 1995, bankruptcy announced one of the oldest English banks, Barings, whose losses on the derivatives market exceeded USD 1 billion. At the same time, Orange County was bankrupt due to losses exceeding 1.7 billion dollars (Redhead, 1997, p. 15).

Many institutions have begun to realize the consequences of the misuse of derivative instruments in response to these events. The first reactions were very nervous, as some companies even gave up trading in options and futures contracts, while others significantly reduced their exposure to the derivatives market. It did not have an impact on the financial risk they incur. However, it is likely that enterprises will likely look more favorably at derivative markets in the near future, including exotic options. It can be estimated that the share of these instruments in the total turnover on the options market will increase to a further ten or twenty per cent - currently, depending on the market segment, it is 5-10%. Asian options, barrier options, basket options, binary options, and rainbow options are the most important on the exotic options market. In the role of underlying instruments, there are goods, exchange rates, shares, stock indices, debt securities and interest rates.

To sum up this lengthy history segment - derivative instruments, including futures, appeared on a larger scale on the financial markets in the 1970s. The reason for their introduction was the increased volatility of exchange rates, interest rates, stock prices and commodity prices that could be observed on global markets during this period. An increase in volatility in financial instruments' prices means an increased risk of investing in these financial instruments.

As derivative instruments issued for commodities were previously traded on commodity exchanges, the existing patterns were used - their task was to reduce the risk associated with changes in commodity prices and, more strictly, to hedge against the rise or fall of commodity prices. In order to limit the risk, derivatives have been introduced. A derivative is a financial instrument whose value depends on the value of another financial instrument, called the underlying (underlying) instrument (Lynn, 2006, p. 55). A primary instrument is sometimes a physically existing financial instrument, such as stock, bond or currency. It is not uncommon, however, that the primary instrument is an index from the financial market.

1.1. Futures contracts as derivative financial instruments

In finance, a derivative is a type of financial instrument that value depends on the price of an underlying asset. Examples of underlying assets include assets, indexes, or interest rates (Arditti, 1996, p. 44). The main categories of derivative instruments are: forwards, futures, options and swaps. (Kolb, 2000, p. 2)

Derivative financial instruments may serve many purposes, making them a popular choice for many financial and non-financial corporations. The following list includes the most important ones connected with futures contracts (Chew, 2008, p. 66):

- Insurance against price movements,
- Increase exposure to price movements for speculation,
- Getting access to assets or markets that are otherwise hard to trade.

The central place for trading derivatives is the New York Stock Exchange and the likes, but it is also possible to trade them off-exchange. Moreover, as an aftermath of the US financial crisis of 2007-2009, the idea of moving derivatives to exchanges appeared (Pavaskar, 2016, p. 58). Derivatives are one of the three most popular categories of financial instruments. Derivatives come in various shapes and sizes; however, the most common ones include forwards, futures, options, swaps, and variations like synthetic collateralized debt obligations or credit default swaps. The other two are stocks like equities or shares and debts like bonds and mortgages (Chew, 2008, p. 45).

Derivatives can also be described as contracts involving two parties whose main aim is to determine detailed conditions necessary to move forward with the endeavour at hand. Such details may include dates, values that result from the complete translation and definitions of variables that underlay the trade, obligations that result from contracts and the notional amount. The information described above is necessary for payments to be made between the (Kolb & Overdahl, 2003) parties involved in the business.

Assets under consideration can be in many forms, such as stocks and bonds, but also in commodities, interest rates or different currencies. It is also possible to consider other complex assets as underlying for the derivatives, but it may add an extra layer of difficulty to correct valuation (Durbin, 2011, p. 32).

All derivatives connected with finances are cash flows, which are discounted and conditioned stochastically to present value. It is possible to trade the market risk inherent in the underlying asset because it is attached to the financial derivative due to contractual agreements made between the parties. The underlying asset does not have to be acquired as derivatives allow the ownership and participation in the market value of an asset to be severed. Moreover, there is significant space to write down the contract in a matter suitable for both parties, and it means that there are not many limits and restrictions as to how contractual agreements should look like or what they should include (Durbin, 2011, p. 32).

Due to that freedom, it is possible for those responsible for designing derivatives to adjust the level and nature of participation in the underlying asset's performance. Therefore, there's a way to weaken, strengthen, or even inverse the participation in the underlying market value. This operation is called the leverage effect, and because of its implementation, control of the market price risk of the underlying asset is possible in nearly every situation.

In general, derivative contracts can be put into two groups. The first type includes OTC derivatives, which are traded over-the-counter, thus the abbreviation. It means that they are traded directly, without the involvement of any intermediary or an exchange. Those include swaps, forward rate agreements or exotic options such as exotic derivatives. The size of its market highlights the importance of OTC derivatives. The OTC derivative market is the largest one for derivatives. This market is not regulated due to disclosure of information that obligates all parties because the OTC market includes mostly banks and other entities like that. As for statistics and reporting, gathering and collecting them is difficult because OTC amounts are traded in private, and the OTC market activity is not visible on any exchange (Durbin, 2011, p. 34).

The second group of derivatives is called exchange-traded derivatives, ETD in short. Those undergo trade by means of derivatives exchanges or other kinds of exchanges (Durbin, 2011, p. 35). The ETD market is a place for trading standardized contracts defined by the exchange. Derivatives exchanges play the role of intermediaries for all transactions related to the given trade operation and take initial margin from both sides as a guarantee. The following table presents the world's largest derivatives exchanges based on the number of transactions carried out (F&O Week, 2020).

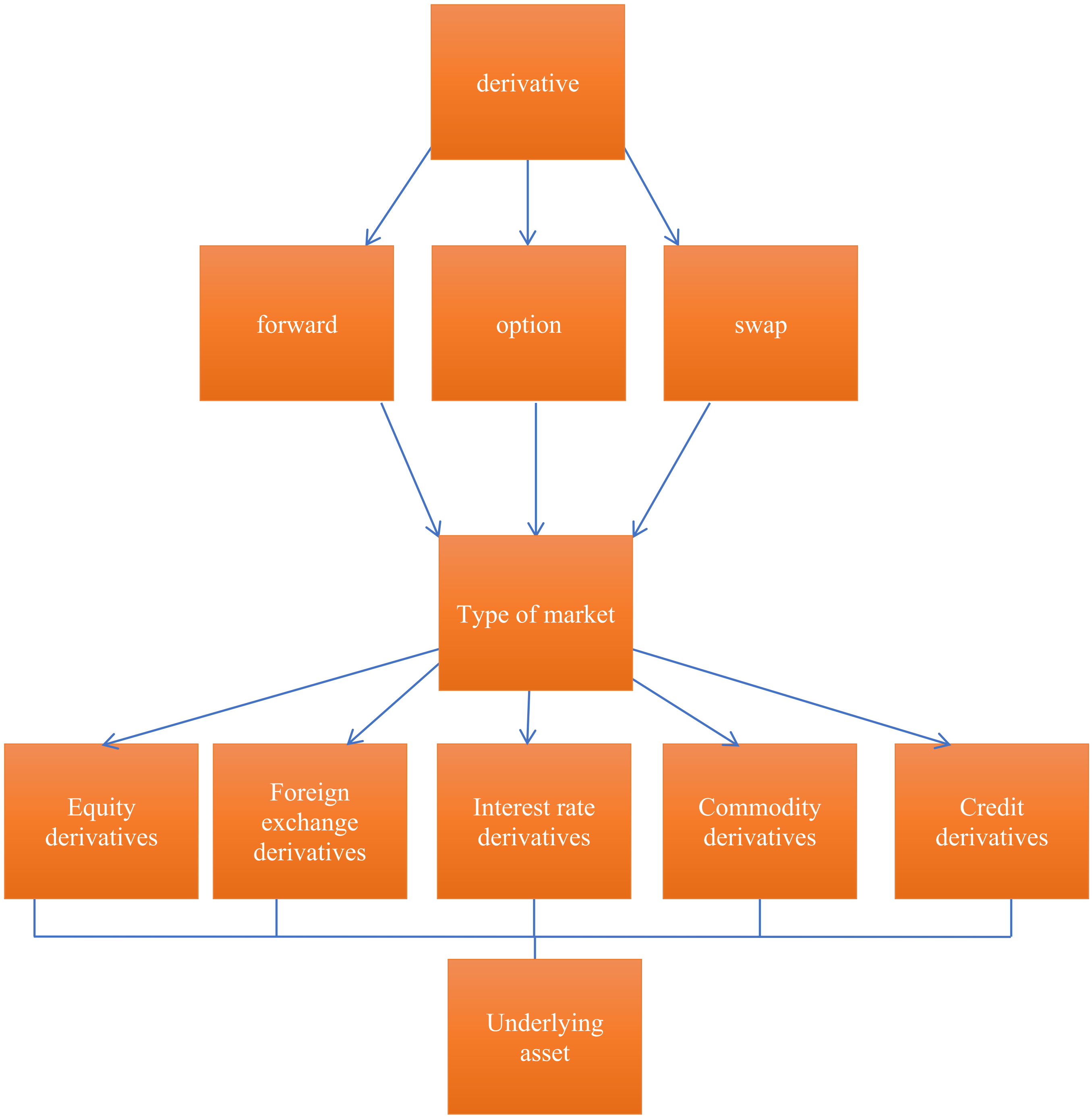
Table 1.1: World largest derivatives exchanges based on the number of transactions.

Name	Range
The Korea Exchange	KOPSI Index futures & options
Eurex	European products (interest rate & index products)
CME Group (the result of the merger between the Chicago Mercantile Exchange, the Chicago Board of Trade and the New York Mercantile Exchange	Futures and options trading for risk management

Derivative contracts can be traced back a couple of centuries. Nowadays, they are not anything unusual and have become very popular and common. Some of the oldest derivatives can be traced to China, where the Dojima Rice exchange has been trading rice futures since the eighteenth century (Suzuki & Turner, 2005).

Nowadays, derivatives can be classified as ETD or OTC depending on the relationship between the underlying asset and the derivative. Moreover, the whole process is characterized by their payoff profile. The following chart presents the possible options of derivatives (Hull, 2011).

Figure 1.1: Ways to create complex derivatives.



In the broader sense, derivatives can be either *lock* or *option* type of products. The former group includes the already mentioned swaps, futures and forwards. Its main feature is that it makes the parties enter into obligations of the contract that last during its life. The latter group, options products, includes several kinds of derivatives, for instance, interest rate swaps. As the name suggests, such derivatives give the purchasing party an option, or rather the right, to enter the contract under the previously agreed terms, but it is not its obligation to enter the contract under such terms (Shirreff, 2004, p. 23).

As for their application, derivatives are generally used either to manage risk or speculation. The former is called hedging, and it is executed by providing offsetting compensation if an unwanted event occurs. Therefore, it can be considered a kind of insurance. The latter is based on making a financial bet associated with the transaction. It is essential to set apart the two types because risk management focuses on prudent aspects of transactions and management of finances for many companies from different sectors of the economy. On the other hand, speculation presents a chance, although risky, for managers and investors to increase their profits by placing bets and withholding this information from stakeholders because its disclosure is not mandatory (Chance & Brooks, 2010, pp. 483-515).

Derivatives have various applications, with the most important listed below:

- Risk hedging or mitigation – concerns the underlying. Execution of a derivative contract, in which the value moves away from the position of the underlying, may cancel part or even the whole underlying out (Chernenko & Faulkender, 2011).
- Creating an option in which the derivative value is connected to a clearly defined condition or event such as the underlying achieving a required price level (Mattoo, 1997, p. 102),
- Obtaining exposure to the underlying, which makes it impossible to trade in the underlying (Mattoo, 1997, p. 104),
- Applying leverage or gearing according to which even an insignificant movement of the underlying value may be the cause of a significant difference in the value of the derivative (Chernenko & Faulkender, 2011, p. 1736),

- Speculating and profiting if everything goes as expected. It means that the value of the underlying asset increases or decreases within or outside of a specified range according to the previously assumed expectations (Chance & Brooks, 2010, p. 485),
- witching assets and their allocation between various classes without disrupting the underlying assets. This operation is considered a type of transition management (Mattoo, 1997, p. 104),
- Avoiding paying taxes (Chance & Brooks, 2010, p. 490).

There are many various variants of derivative contracts. Due to their unregulated character and flexibility, it is difficult to name all of them because everyone has some slight or significant alterations that make them different from other types of derivatives.

However, it is still possible to name the most common types of derivative contracts based on their features. The following table presents those types of contracts.

Table 1.2: Common types of derivative contracts (Hull, 2011)

Name	**Features**
Forwards	It is a tailored agreement between two parties. Payment takes place at a previously agreed date but at the price that is valid today. Forwards are not standardized contracts; both parties make contributions to the final signed contract.

Futures	Sales or purchase agreements for assets to be purchased or sold in the future at a specified time but at a price agreed upon on the day of agreement conclusion. It differs from forwards because it is a standardized contract supervised by an exchange where the agreement may be purchased or sold.
Options	Those types of derivative contracts grant the owner the right to purchase (call option) or sell (put option) an asset. However, he or she is not obliged to do so. The price is determined at the time of concluding an option contract, and it is called the strike price. In addition to that, options also have a maturity date, which differs from the version valid overseas. **European options**: grant the owner the right to require that the sales operation takes place not before and not after but precisely on the maturity date.

Options	**American options:** unlike in European options, the owner has the right to require the sale to be carried out at any time before the maturity date. In the case of exercising this right, the other party of the contract is obliged to execute the transaction. **Call option:** the buyer has the right to purchase a non-specified quantity of the underlying asset at a specified price before or on a specified future date without the obligation to exercise this right. **Put option:** the seller has the right to sell a non-specified quantity of the underlying asset at a specified price before or on a specified future date without the obligation to exercise this right.
Binary options	Include an all-or-nothing profit profile. Either the parties gain profits or gain nothing from the transaction.

Warrants	It is an option derivative that is long-dated and traded over the counter.
Swaps	Agreements that are connected with exchanging cash flows on or within the period before a determined date in the future on the basis of the underlying value of the exchange rates applicable to the given currencies or bonds/interest rates, commodities exchange, stocks and other assets.
Swaptions	It is a term associated with swaps, and similarly to call and put options. There are two ypes of them: **Receiver swaption:** it is possible to receive fixed and pay floating **Payer swaption:** it is possible to pay fixed and receive floating.

Interest rate swap	Swaps involving interest associated cash flows between two parties, always in the same currency.
Currency swap	Cash flow between the two parties of the contract constricts principal and interest. Unlike interest rate swaps, money is in different currencies for both parties of the contract.

In addition to the information presented above, which is irreplaceable in the process of understanding derivative contracts and their features, the author would also like to mention some economic functions of the derivative market. It has to be mentioned that prices of that market not only reflect the discernment of its participants and the future but also direct the underlying prices to the declared future levels. Moreover, upon the expiration of the derivative contract, derivative prices and underlying prices congregate with one another. That being said, it is evident that derivatives cannot be replaced as a tool for determining current and future prices. There is a connection between the derivatives market and the spot market due to the intrinsic nature of the former. Pointing to the fact that the underlying spot market is connected to the derivatives market, it is possible to observe an increase in traded volumes on the spot market. This situation is the result of increased participation of additional players, who are attracted to the market due to the absence of any procedures for transferring risk (Simkovic & Kaminetzky, 2010, p. 118).

1.2. Main categories of futures transactions

The following part of the thesis shall focus on categories of futures transactions: types and features of the most common types of transactions that can be considered futures transactions. This chapter has already mentioned that there are many different kinds of derivative contracts, which align with futures transactions to a certain degree. The main categories mentioned here shall include forward and futures contracts; however, they shall be presented in more detail than in the previous part of this chapter, where they have been included as examples of derivative contracts and described briefly.

1.2.1. Forward contracts

The most basic forward contract is a forward delivery contract (Kolb & Overdahl, 2003, p. 15). It is a non-standardized agreement between two parties that governs the transfer of ownership of assets at a previously agreed future time and at a price agreed upon when the contract is signed. The party that wants to purchase the underlying asset later takes on the long position, and the other parties, that is, the one that wants to sell the underlying asset in the future, assumes the short position. The parties that agree to enter into the forward delivery contract are known as counterparties (Kolb & Overdahl, 2003, p. 15). The price agreed between the two parties is known as the delivery price and equals the forward price when concluding the contract. As for the payment for the underlying asset, it takes place before handing over the control of the asset to the other party (Hull, 2000, p. 3).

Similarly to the other already described derivatives, forwards are used to either hedge risk through speculation or enable the party to benefit from the quality of the underlying asset (Hull, 2000, p. 4)

There is much similarity between forwards and futures contracts; however, they are different in some aspects and features. Forwards, unlike futures, are not exchange-traded and are not standardized. It means that they are not based on a clearly defined standardized asset. They usually do not have partial settlements or margin requirements, and parties do not have to exchange extra property for securing its interest; thus, the entire yet-to-be-realized gain or loss builds up while the contract is still open (Redhead, 1997, pp. 40-45).

On the other hand, due to trading forwards over the counter, their specification can be customized to include marked-to-market and daily margin calls. Thus, one party can include a clause in the contract, which calls for additional collateral from the loss party to provide better security to the party at gain. Certain events like fluctuations in credit ratings, the value of managed assets or redemptions over a specified period determine collateral for forward contracts. (Redhead, 1997, p. 45).

The price of a forward contract is agreed upon between the parties using the rational pricing assumption. The price concerns an underlying asset, which is tradable. If the underlying asset can be traded and there are dividends in place, the forward price is calculated using the following formula (Lioui & Poncet, 2005, p. 86):

$$F = S_0 e^{(r+q)T} - \sum_{i=1}^{N} D_i \, e^{(r-q)(T-t_i)}$$

Where:

F – forward price to be paid at time T

$\boldsymbol{e^x}$ – exponential function

r – risk-free interest rate

q – cost of carry

$\boldsymbol{S_0}$ – spot price of the asset

$\boldsymbol{D_i}$ – divided guaranteed to be paid at time t_i where $0 < t_i < T$

1.2.2. Futures contracts

A futures contract is essentially a forward contract that is traded on an organized financial exchange (Kolb & Overdahl, 2003, p. 17). Marking to market creates a fundamental difference between futures and forward contracts letting traders lock in prices. With a forward contract, the price of the asset exchanged at delivery is the price stated in the contract. With a futures contract, the purchaser pays, and the seller receives the spot price prevailing at the delivery date. All gains and losses on a futures position are recognized after the conclusion of every trading day so that over the life of the futures contract, the accumulated profits or losses—coupled with the spot price at delivery—yield a net price corresponding with the futures price quoted at the time the futures position was established (Kolb & Overdahl, 2003, p. 19).

According to Björk, a futures contract can be described as delivery of item ***J*** at the time ***T***. Moreover, a futures contract must meet the following conditions to exist and be considered a valid futures contract (Arditti, 1996, p. 67).

- There is a quoted price in the market ***F(t,T)*** known as the futures price at time ***t*** for delivery J at time T.
- The price of entering such a contract equals zero.
- At any time intervals [t, s] the holder receives the amount F (s, T) – F(t, T)
- At time ***T***, the holder pays ***F(T,T)*** and is entitled to receive the traded item

Pricing of futures contracts is calculated using the following formula (Arditti, 1996, p. 68):

$$F = S \times (1 + \frac{r}{t})$$

Where:

- ***F*** – commodity price
- ***S*** – current value of the underlying asset
- ***r*** – annual risk-free return
- ***t*** – maturity

The above formula can be adequately modified depending on the type of futures contract and the anticipated events. A widespread version of the formula is:

$$F = S \times e^{rT}$$

where $\boldsymbol{T}$ is the contract maturity.

Codes other than monthly used in futures contracts have been selected by the author and presented in the tables below. The codes regard commodities, currencies and the most important exchanges (Financial Academy, 2019). Codes for months can be found in the corresponding subchapter, delivery date.

Table 1.3: Contract codes for exchanges

Abbreviation	**Exchange**
CBOT	**Chicago Board of Trade - Division of CME Group**
CME	**Chicago Mercantile Group**
NYBOT	**New York Board of Trade**
KCBT	**Kansas City Board of Trade**
MGE	**Minneapolis Grain Exchange**
MATIF	**ParisBourse SA**

SFE	**Sydney Futures Exchange**
NYM	**NYMEX Division – New York Mercantile Exchange Division of CME Group**
LIFFE	**London Int'l Financial Futures Exchange**
EUREX	**Eurex**
ICE	**Int'l Commodity Exchange**

Table 1.4: Codes for commodities (Financial Academy, 2019).

Symbol	**Futures Contract**	**Exchange**	**Futures Delivery Month**	**Minimal Ticket**	**Unit Move**
Currencies					
AD	**Australian Dollar**	**CME**	**H, M, U, Z**	**0.01**	**$1000**
BP	**British Pound**	**CME**	**H, M, U, Z**	**0.01**	**$625**
CD	**Canadian Dollar**	**CME**	**H, M, U, Z**	**0.01**	**$1000**
DX	**US Dollar Index**	**ICE**	**H, M, U, Z**	**0.01**	**$1000**
EU	**EuroFx**	**CME**	**H, M, U, Z**	**0.01**	**$1250**
JY	**Japanese Yen**	**CME**	**H, M, U, Z**	**0.01**	**$1250**
SF	**Swiss Franc**	**CME**	**H, M, U, Z**	**0.01**	**$1250**
Energies					
CL	**Crude Oil**	**NYM**	**F, G, H, J, K, M, N, Q, U, V, X, Z**	**0.01**	**1000**
HO	**NY Harbor ULSD/Heating Oil**	**NYM**	**F, G, H, J, K, M, N, Q, U, V, X, Z**	**0.01**	**420**
HU	**Unleaded Gas**	**NYM**	**F, G, H, J, K, M, N, Q, U, V, X, Z**	**0.01**	**420**

NG	Natural Gas	F, G, H, J, K, M, N, Q, U, V, X, Z	0.01	0.001	10,000
RB	RBOB Gasoline	NYM	F, G, H, J, K, M, N, Q, U, V, X, Z	0.01	420
ITCO	Brent Crude	ICE	F, G, H, J, K, M, N, Q, U, V, X, Z	0.01	1000
Grains and Soy Complex					
BO	Soybean Oil	CBOT	F, H, K, N, Q, U, V, Z	0.01	600
C	Corn		F, H, K, N, U, X, Z	1/4	50
KW	Kansas City Wheat	KCBT	H, K, N, U, Z	1/4	50
O	Oats	CBOT	H, K, N, U, Z	1/4	50
MW	Minneapolis Wheat	MGE	H, K, N, U, Z	1/4	50
S	Soybeans	CBOT	F, H, K, N, Q, U, X	1/4	50
SM	Soybean Meal	CBOT	F, H, K, N, Q, U, V, Z	0.1	100
W	Wheat	CBOT	H, K, N, U, Z	1/4	50

Metals					
GC	**Gold**	**CMX**	**G, J, M, Q, V, Z**	**0.1**	**100**
HG	**Copper**	**CMX**	**H, K, N, U, Z**	**0.05**	**250**
PL	**Platinum**	**NYM**	**F, J, N, V**	**0.1**	**20**
SI	**Silver**	**CMX**	**H, K, N, U, Z**	**0.005**	**50**
Meats					
FC	**Feeder Cattle**	**CME**	**F, H, J, K, Q, U, V, X**	**0.025**	**500**
LC	**Live Cattle**	**CME**	**G, J, M, Q, V, Z**	**0.025**	**400**
HE	**Lean Hogs**	**CME**	**G, J, K, M, N, Q, V, Z**	**0.025**	**400**
PB	**Pork Bellies**	**CME**	**G, H, K, N, Q**	**0.025**	**400**
Da	**Milk Class III**	**CME**	**F, G, H, J, K, M, N, Q, U, V, X, Z**	**0.01**	**2000**

1.2.3. Futures prices

There are various ways of pricing when it comes to futures contracts. One of them is considered when the deliverable asset is in plentiful supply or its creation does not require any costs. In this situation, the price of a futures contract is settled in the way of arbitrage arguments. This way of conduct is typical for stock index futures, treasury bond features and physical commodity futures. As it has already been mentioned, such commodities have to be in plentiful supply, and an example can be crops just after the harvest period. However, if the commodity has not been created yet or its supply is low, e.g. crops before the harvest, the price cannot be established by arbitrage. The main indicator for price in this situation is supply and demand (Arditti, 1996, p. 70).

Arbitrage arguments are also known as rational pricing. In those operations, the forward price is the expected future value of the underlying discounted at the risk-free rate. The forward price is the strike K so that the contract's value is 0 at the present time. The forward price of the futures equals the forward price of the forward contract of identical strike and maturity if interest rates are assumed to be constant. Moreover, it's also identical if the underlying asset is not connected with interest rates. In other cases, the difference between the futures price and forward price on the asset is proportional to the covariance between the underlying asset price and the interest rate (Lioui & Poncet, 2005, p. 106). Therefore, if one assumes constant rates such as non-dividend paying asset, the value of the futures or forward price is calculated in the following way (Arditti, 1996, p. 71):

$$F(t,T) = S(t) \times (1+r)^{(T-t)}$$

where:

F(t,T) – value of the futures/forward price

S(t) The present value of underlying asset

t – time of entering into position

T – time of maturity

r – risk-free return rate

The concept of base for Futures

This is the difference between the derivative and the underlying rate. In the following example it will be the difference between the price of the earliest contract futures on the E-mini DOW index and the value of the index itself:

base = contract price (futures price) - index value (spot price)

For example, at the closing of the session, the E-mini DOW contract series was valued at 2552 points, and the index value was 2562 points. The base was therefore negative and amounted to:

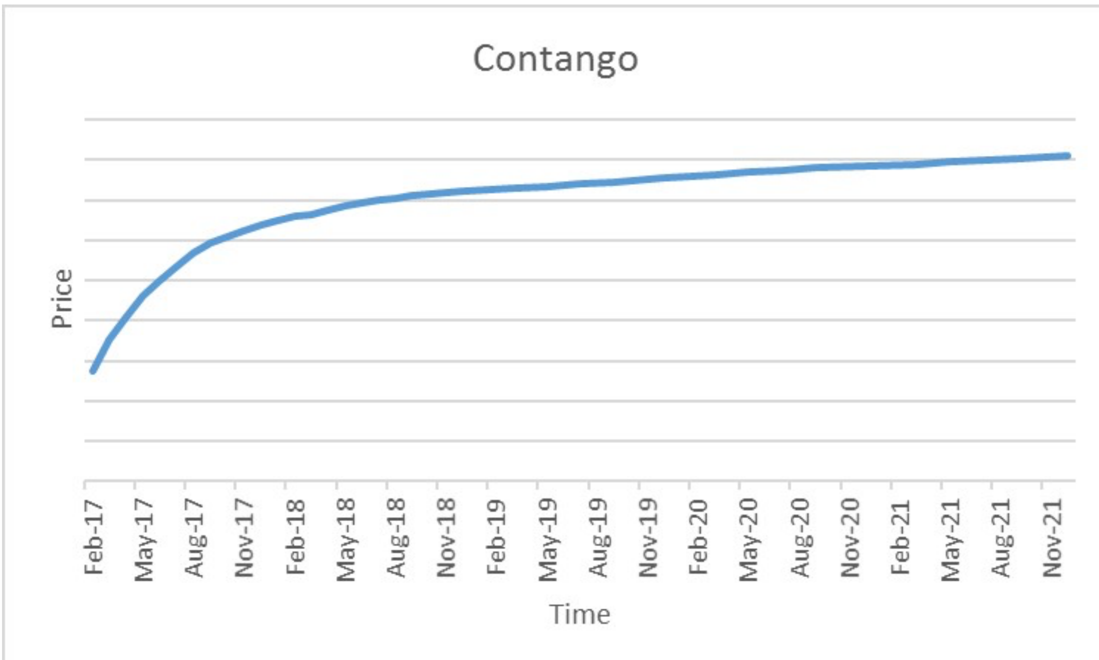
10pts: base = 2552 – 2562 = –10

It is widely accepted that a positive base on contracts indicates the optimism prevailing on the market and vice versa; if the majority of market participants expect imminent declines, then the contracts are valued below the index. Since the risk-free interest rate usually exceeds the dividend rate, in theory, the base should be positive and gradually decrease as the expiry date of a given series of derivative instruments expires. The reality, however, is far from these assumptions. The rates of contracts and index are, of course, very similar but rarely the same. Contracts are usually valued below or above the underlying instrument. This discrepancy is clearly noticeable on the domestic floor, where the practical absence of short sales of shares limits the possibility of arbitrage. Arbitrageists use the base that is favorable for them, which leads to adjusting the market valuation of contracts to their theoretical value (marketwatch, 2019).

The futures curve, sometimes called the forward curve, is an impotent concept in the way futures markets are analyzed. The futures curve is the difference between a forward price of a futures contract and the current spot price of the underlying commodity. It is regarded to be an indicator of the market sentiment for the future price of the underlying asset.

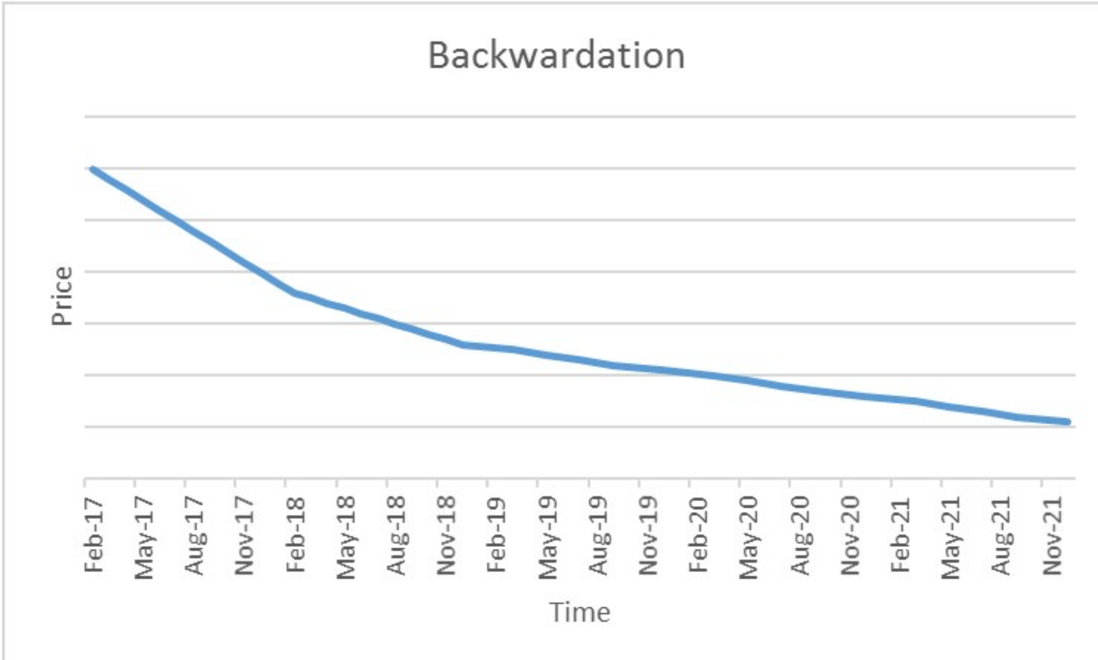
The shape of the futures curve is critical to hedgers and speculators. Two main types of markets are Contango and Backwardation. Contango market is when the futures price is above the expected future spot price.

Figure 1.2: Contango (Chicago Mercantile Exchange, 2020)



Normal backwardation is when the futures price is below the current spot price for the commodity. In the chart below, the spot price is higher than future prices and has generated a downward sloping forward, or inverted, curve which is in backwardation. The futures forward curve may become backwardated in physically delivered contracts because there may be a benefit to owning the physical material, such as keeping a production process run.

Figure 1.3: Backwardation (Chicago Mercantile Exchange, 2020)



1.2.4. Settlement date

In finances, settlement is the act of finalizing a contract and it can be carried out in one of the two following ways. The method of finalization depends on the type of futures contract.

The first type is physical delivery. In it, the seller delivers the amount of the underlying asset to the exchange, and the exchange forwards it to the buyer. It is a typical way of settling commodities and bonds. However, on a daily basis, it is completed only with the friction of contracts. Most of the time, contracts are cancelled by purchasing a covering position, that is, buying a contract to cancel out an earlier sale, which is called covering a short. On the other hand, there's the act of selling a contract to cancel out an earlier purchase, thus, covering a long (Arditti, 1996, p. 130).

The second type is cash settlement, where cash payments are issued on the basis of the underlying reference rate. An example here is the closing value of a stock market index. The way of settling is carried out by payments made or received of loss or gains connected to the contract upon the contract expiration date (Lioui & Poncet, 2005, p. 114). As one may assume, cash settlement apply to futures contracts that cannot involve the delivery of the referenced item, such as an index (Lioui & Poncet, 2005, p. 115).

1.2.5. Delivery date

The delivery date, or as it is also often called the delivery month, is the month when the selling party has to deliver commodities to the buying party and issue a payment for the underlying. If the contract does not include physical delivery, then the delivery date is the date of a final mark-to-market. It is impossible to unambiguously define delivery dates because each contract has different delivery dates specified by the exchange in the contract specifications (Lioui & Poncet, 2005, p. 115).

The majority of futures contracts traded on US futures exchanges, like short-term interest rates or foreign exchange, typically expire quarterly, that is, in March, June, September, and December. Some contracts traded on non-US exchanges have expiration dates that are not quarterly (Lioui & Poncet, 2005, p. 116).

Nearly all futures contacts are marked with five characters. The first two letters are identification letters for the type of contract, and the remaining three identify the month and the year, respectively. Codes for each month are marked with the letters of the alphabet. However, as one may presume, they are not the first letters of each name of the month like it’s usually the case. Each month has the following designation (Redhead, 1997, p. 21):

- January = F
- February = G
- March = H
- April = J
- May = K
- June = M
- July = N

- August = Q
- September = U
- October = V
- November = X
- December = Z

1.2.6. Intermediaries of futures contracts

In all types of financial transactions, an intermediary is an entity that carries out another person's will in its behalf. Here, an intermediary acts as an agent with futures, swaps or options trading. In order to become an intermediary, one has to register and become subject to various financial requirements, such as disclosure of finances, reporting cash flows, keeping records of contracts. Commodity Exchange Act defines intermediaries as follows (Federal Reserve, n.d.):

- Futures Commission Merchant (FCM) – their duties include soliciting or accepting orders for futures or options traded on exchanges or subject to their rules. They accept money, securities and property to margin, guarantee or secure contracts and trades
- Introducing Broker (IB) – solicits or accepts an order for futures or options traded on exchanges or subject to their rules. The difference between FCMs and IBs is that an IB does not accept any money, securities or properties
- Commodity Pool Operator (CPO) – is part of operations of a collective investment vehicle and accepts or solicits funds, securities or property in order to purchase interests of that collective investment vehicle
- Commodity Trading Advisor (CTA) – deals with compensations and profits. Their duties include advising others directly or through publications, writings, electronic media or other carriers of information regarding trading futures or options contracts on exchanges or those subject to the rules of exchanges. Moreover, as part of his regular business activity, a commodity trading advisor issues reports and analyses about the above-described activities.

- Swap Dealer (SD) – this type of intermediary acts as a dealer in swaps, makes a market in swaps and enters into swaps with counterparties regularly and for his account. He is concerned with all activities that require a swap dealer.
- Major Swap Participant (MSP) – such an intermediary has many duties and rights on the exchange. He holds an influential position for hedging or mitigating commercial risk.

1.3. The calculation of futures contracts

Before actually attempting to calculate the profit of holding a futures contract, it is necessary to calculate the futures value. The best way to show it is by an example. From the previous parts of this chapter, it is already clear what hedging is; therefore, it is essential to understand that all calculations connected with futures are mostly connected with protecting one's long position against sudden, negative changes on the market (Hull, 2000, p. 49; Kolb, 2000).

In our example, the value of the owned stock comes to $240,000 in the S&P 500 Index market at the price of 1400.00. In order to "hedge" our stock, it is essential to calculate the futures value at 1400.00 for the E-mini SP500. The full rotation of the contract costs $50, which is the change from 1400.00 to 1401.00. The best way to understand that is to determine the so-called ticks, which occur during every rotation, which is also called "handle." The contract from the example has four ticks; therefore, it is easy to calculate the value of ticks.

If the change is from 0 to 1, then:

$$1 \div 4 = 0.25$$

The value of one tick is 0.25, and thus the cost of the full rotation is:

$$\$50 \div 0.25 = \$12.50$$

The tick movement is as follows:

1400.00 → 1400.25

1400.25 → 1400.50

14.00.50 →1400.75

1400.75 → 1401.00

The next step is to multiply 1400.00 by the value of the full rotation, which is \$50. Therefore,

$$\$50 \times 1400.00 = \$60.000$$

After that, using the value of \$240.000, the value of the owned stock, we can calculate how many E-mini SP500 futures contracts have to be sold to hedge the portfolio of \$240.000. That being said,

$$\$240.000 \times \$60.000 = 4$$

Thus, the number of futures contracts to be sold comes to four. Given that one full rotation came to \$50, it would be necessary to possess at least \$2.000 in the account to hedge the position of \$240.000 safely. An important note is that each futures contract includes collateral, or a margin, which is required in order to complete funding. The approximate collateral or margin of contracts of this type comes to around \$500; it depends on the type of trading an individual engages in (Lioui & Poncet, 2005, p. 120).

To summarize the above example, in order to calculate the futures contract, one has to multiply the price of the owned stock by its total rotation price. In the example above, the total rotation came to \$50. Subsequently, the value of the owned stock has to be divided by the number acquired from the previous equation, in this example, \$60.000. The result is the number of stocks that allow for safe hedging of the position of \$240.000, that is \$2.000.

Another aspect of calculating futures contracts is connected with profit and loss. Like in the case of every financial transaction, the merits of operation are measured by profits and losses.

In the case of futures contracts, people engage in trading on futures markets to make a profit or hedge against losses (Lioui & Poncet, 2005, p. 121)

From the example above it is already known how to calculate the value of futures contracts that may protect from losses; in other words, what is the hedge value of a given futures contract.

An important fact to bear in mind is that each market calculates price and size movements differently, and therefore the presented values of losses also differ from one market to another. Therefore, each trader has to be aware of that and get familiar with the rules of calculating loss and profit on a corresponding market. Essential features that have to take into consideration when calculating profit and loss for futures contracts include (Hull, 2011, p. 49):

- Contract size,
- Ticket size,
- Trading price at the moment,
- sale or purchase value of the contract.

Let us follow the example presented in *Financial Derivatives: An Introduction to Futures, Forwards, Options and Swaps*. According to this source (Redhead, 1997, p. 150), WTI Crude Oil futures is expressed as the expected value of 1.000 barrels of oil, where prices of futures contracts are quoted in dollars per barrel. As for the tick size, it comes to $0.01. Now, it's possible to calculate several values based on that information, such as the current value and the value of a one-tick move.

If, for instance, the current price of Crude Oil comes to 60$, then to calculate the current value of such futures contract, the current price of an oil barrel has to be multiplied by the contract size.

It has already been mentioned that 1.000 barrels of oil is the contract size, thus.

$$\$60 \times 1000 = \$60.00$$

gives the current value of $60,000.

In order to calculate the value of a one-tick move, the tick size and the contract size must be multiplied. The contract size comes to 1000 oil barrels, and one tick in WTI Crude Oil is $0.01. Therefore,

$$1000 \times \$0.01 = \$10$$

the tick value of one move is $10 (Redhead, 1997, p. 150).

After obtaining the values mentioned above, one can calculate profit and loss related to trading operations. For that, the value of a one-tick move has to be multiplied by the number of ticks of a given futures contract. The number of ticks is expressed as the total amount of ticks a given futures contract has moved since purchase. The result is profit and loss gained per one contract, and in order to obtain the total profit and loss value one has to multiply the obtained value per contract by the number of owned futures contracts (Redhead, 1997, p. 151).

Consider the following example:

WTI Crude Oil futures contract was bought at the price of $56.50. After some time, the price of WTI came to $57. In order to calculate profit at that time, we have to subtract the former value from the latter, thus,

$$\$57 - \$56.50 = \$0.50$$

the profit per one contract is $0.50.

As a reminder, the value of the tick is $0.01, therefore,

$$\$0.50 \div \$0.01 = 50$$

the number of ticks the contract has moved is 50.

Now, in order to calculate the total tick move value in dollars, one has to multiply 50 ticks by the established value of one tick move, that is, $10.

$$50 \times \$10 = \$500$$

The result is the profit obtained from one futures contract. Now, in order to calculate the total profit, it is necessary to multiply the total tick move value by the number of owned futures contracts.

Another calculation related to futures contracts concerns the value of a marketer's entering position. Different futures contracts have different sizes of contracts, and thus their effect on both profit and loss of a specific category of futures contracts. The first step for a successful entry is to understand that price fluctuation and market volatility both affect the value of everyone's open trading position. Average True Range (ATR) is a technical analysis indicator that measures market volatility using decomposition of the entire range of an asset for a defined period. .[Wilder, https://www.investopedia.com/terms/a/atr.asp] The true range indicator is taken as the greatest of the following: current high less the current low; the absolute value of the current high less the previous close; and the absolute value of the current low less the previous close. The ATR is then a moving average, generally using 14 days, of the true ranges.

Consider the following example, using Average True Range (ATR) for Silver futures (Redhead, 1997, p. 200):

The 14-day ATR for Silver futures comes to $0.16, multiplied by 1.000 gives 160 ticks. According to the literature, the value of a typical daily tick movement equals 160 ticks times $5 per tick, that is,

$$160 \times \$5 = \$800$$

There are also average moves in futures contracts that have larger values, and they can be sizable; therefore, when engaging in operations with them, traders should map out their loss and profit and risk and considerations accordingly (Redhead, 1997, p. 202).

Subsequent necessary calculation when it comes to futures contracts is the customer margin, which is expressed by financial guarantees of both sellers and buyers that ensure fulfilment of obligations under their agreements. The responsibility for controlling and supervising customer margin accounts lies in the hands of futures commission merchants. It is important to remember that margins are determined based on market risk and contract value (Redhead, 1997, p. 203).

The initial margin, a type of performance bond, is required to enter in a futures position. The amount of this type of margin is calculated based on the maximum estimated change in the value of a given contract during one trading day. The exchange sets the value of the initial margin. There are various exchanges, and entering positions are related to products and the exchange that trades them, so the percentage of initial margin is set by that exchange (CME Group, n.d.).

The next aspect of the initial margin involves the case of loss or erosion of the value. In such a situation, the broker shall initiate a margin call to respire the amount of the initial margin, which is available. This type of margin is referred to as "variation margin." Calls for margin require swift action, and they are usually paid and received on the same day. If that is not the case, however, the broker has the right to close enough positions to meet the called amount. After closing a certain position, the liability for any deficits on the position owner's account lies in his or her hands (CME Group, n.d.).

Another type of margin is the so-called 'maintenance margin", ' which defines the value by which the initial margin can go down before making a margin call. Determining this might turn out to be very important in the long term and while making a decision about a margin call. Maintenance margin is a preset minimum margin per outstanding futures contract to be maintained by a client in his or her margin account (CME Group, n.d.).

A different term associated with margins is the return on margin. It is used to evaluate performances due to it being a reflection of gain or loss compared to the exchange's assumed risk reflected in the required margin. Return on margin (ROM) is calculated by dividing the realized return and the initial margin (CME Group, n.d.).

$$ROM = \frac{year}{trade\ duration} - 1$$

Subsequently Annualized return on margin (AROM) is calculated as follows:

$$AROM = (ROM + 1)(\frac{year}{trade\ duration}) - 1$$

An investor buying or selling a contract is required to submit a security deposit to the office as a security for the transaction. The value of the deposit for individual contracts is determined as a percentage of the value of the contract. Since the value of the deposit is only part of the transaction value, it is said that futures contracts have large leverage. This allows achieving large profits, with only a small amount involved, which is only a deposit. Both profits and losses from investments on the forward market (in percentage terms) are multiplied compared to those achieved on the cash market *(Lynn, 2006, p. 159)*.

If the investor does not close the position on the same day, the amount of daily profits or losses will be determined based on the daily settlement price at the end of each session. The process of determining profits and losses is called daily settlements. Futures contracts are used by investors for three purposes:

1. Achieving profit on the change in contract prices - they buy contracts counting for an increase in the rate, they sell contracts hoping for a fall in the rate,
2. Having shares fear price declines and sell futures contracts, or - if they intend to buy shares in the future fearing price increases, buy futures contracts,
3. achieving profit using the difference between the theoretical and market value of the forward contract (marketwatch, 2019).

1.4. Types of futures contracts

There are two main categories of futures contracts. The first one concerns financial futures and the second commodities futures. It is possible to distinguish between the types of financial futures described in the table below.

Table 1.5: Types of financial futures (Arditti, 1996).

Financial future	**Description**
Eurodollar futures	Such futures are US dollars deposited outside the country, mainly in European commercial banks dealing in international transactions. They are guaranteed only by the obligations of the banks that hold them.
US Treasury Futures	Treasury bills and bonds are created using futures instruments and the futures market because the stability of the dollar allows for that. This situation is the result of the fact that in most countries US dollar is the reserve currency.

Foreign Government Debt Futures	Futures contracts concerning debts given outside of the country.
Swap Futures	Includes agreements between two parties that regard the exchange of periodic interest payments.
Forex Futures	Manage the risk associated with forex exchange rate fluctuations and exploit them to gain profits.
Single Stock Futures	The most popular type of financial futures contracts also called security futures. They are connected with equity markets.
Index Futures	Futures based on the stock index.

Classification of derivatives based on the underlying instrument.

Multiple groups of derivatives can be identifiesd due to the existence of many types of basic instruments. According to this criterion, the most important groups of derivatives include:

- derivatives for shares (equity derivatives) - here, the basic instrument is the company's share
- derivatives on stock indices (index derivatives) - here, the main instrument is the stock exchange index
- derivative instruments for currencies (currency derivatives) - here, the basic instrument is currency
- interest rate derivatives - here the basic instrument is the interest rate from the financial market or a debt instrument, such as a bond or treasury bill (Lynn, 2006, p. 72)

Every investor in the market must remember that investing in this market carries a much greater risk than stock trading. The risk results, among others from the leverage mentioned earlier, may allow for large profits but may also lead to losses in the event of an unanticipated price change while maintaining a position on the market. The losses may exceed the amount of money invested initially

- wait until the expiration date - the basic instrument is delivered and payment of the contract price for the instrument (determined at the time the contract is concluded) or cash settlement of the contract.
- close the position before the expiry date - the closing of the position consists in the reverse transaction made by one of the parties. In relation to the long side (the buyer), it means the sale of this contract (by placing a sales order). In relation to the short side (the seller), it means purchasing this contract (by placing a purchase order). It should be added that closing the position takes place at the current price of the contract, and therefore each party may gain or lose closing the position before the expiry date.

In the case of futures contracts on the stock exchange, there is a procedure for the daily settlement of the marking to market contract (Lynn, 2006, p. 72). It consists of:

- at the time of the transaction (opening of the position), both parties, long and short, pay a deposit to their accounts in the brokerage houses, which is a small percentage of the value of the contract.
- at the end of the business day, the balances of the accounts of both parties are adjusted depending on the change in the price of the contract during the day; if the price has increased then the balance of the long side is increased, and the balance of the short side is reduced; if the price has dropped, then the balance of the short side is increased, and the balance of the long side is reduced.

- when the balance of any of the parties falls below a certain acceptable level, the party must top it up to the level of the initial deposit (Lynn, 2006, p. 76).

Rules for the use of futures contracts

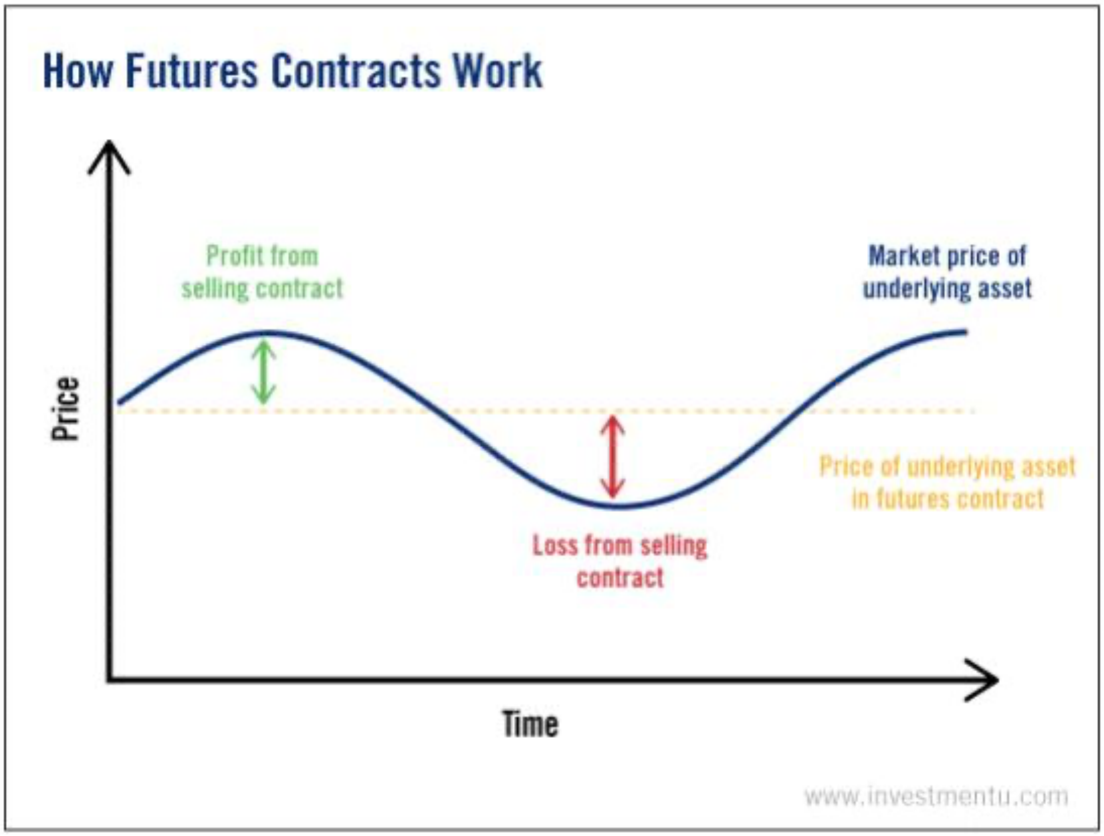
1. Securing against the risk of a decrease in the underlying instrument by selling a futures contract issued for the underlying instrument.

2. Use of futures contracts for speculation: purchase of a futures contract is carried out in anticipation of the price increase of the underlying instrument for which the contract is issued or for sale of a forward contract in anticipation of a decline in the price of the underlying instrument for which the contract is issued (Lynn, 2006, p. 77).

Rate and value of the contract

A very important piece of information for the investor is the price and the value of the contract. Keep in mind that these are not the same values as for the action. The amount of money an investor must have to purchase a contract is derived from the exchange rate, multiplier and margin. Consider the chart below, which presents the forward contract rate (yellow line) and the size of the deposit (the value which the investor has to pay in order to purchase the instrument). Depending on the percentage of the security deposit, it may be higher or lower than the value of the contract price. Please also note that in the ranges for which the value of the deposit is fixed rate and value behave exactly the same (Redhead, 1997, p. 210).

Figure 1.4 How Futures Contracts Work (InvestmentU, 2020)

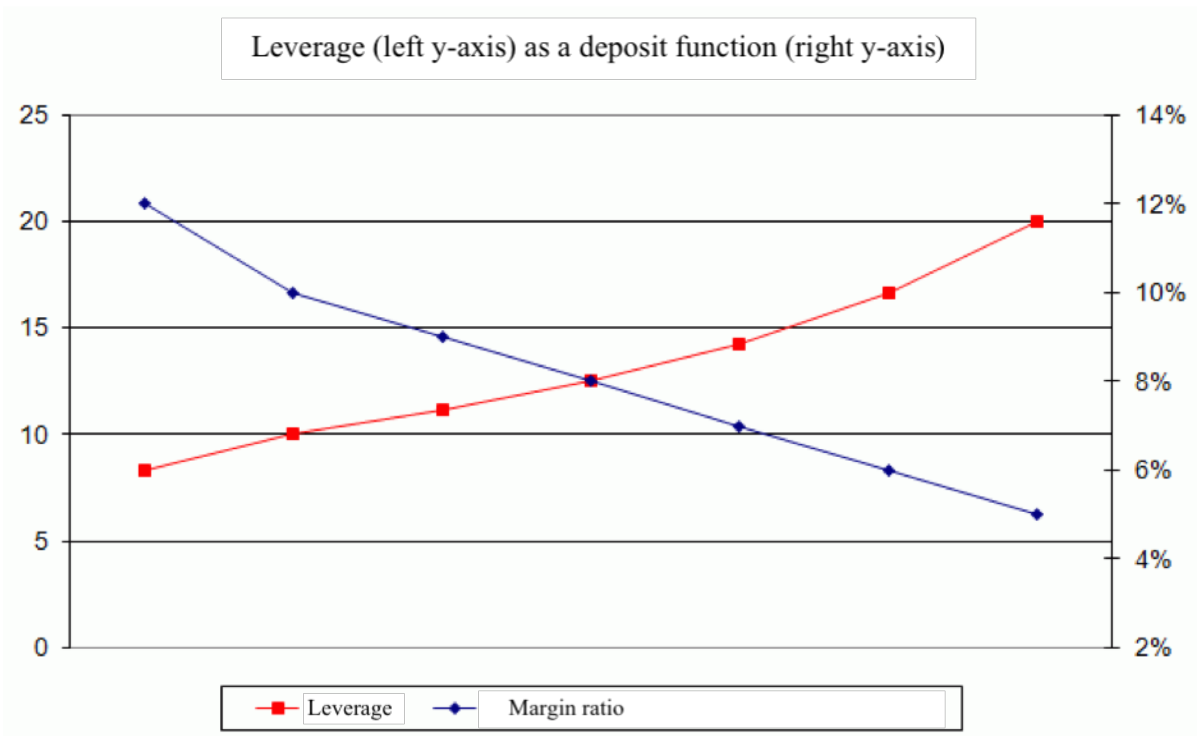


The functioning of futures contracts on the financial market is inseparably connected with the notion of financial leverage, which can be achieved by making a security deposit. The great advantage of futures contracts is that the investor does not need to have a total amount equal to the value of the instrument he/she buys (or the base on which it is based), and only its fraction is called the margin deposit. In contrast to transactions, the settlement of futures transactions is deferred in time. Another advantage is the need to put in a deposit to protect the party from not fulfilling the contract. Therefore, making a deposit is to minimize the risk (Gannon, 2010, p. 112).

Financial leverage

The consequence of a security deposit and not having to pay the full amount for the derivative is a fundamental feature of this market, namely the leverage. Thanks to it, the investor can achieve a much higher rate of return than in the case where he would invest the same amount in the cash market. The leverage mechanism can multiply the potential profit that can be achieved. The chart below shows the leverage as a deposit function. The lower the deposit, the higher the leverage (Gannon, 2010, p. 122).

Figure 1.5: Relationship between Leverage and Margin Ratio



1.4.1. Foreign currency

All transactions involving currencies are called currency futures. Such contracts change hands at a price in one currency but can be bought or sold in another one at a future date. Such contracts bind parties according to the letter of the law and the counterparty, which still holds the contract upon its expiration, has to deliver the currency amount that equals the specified price on the specified date. Such futures are mainly aimed at hedging currency risks but can cover speculation on currency price movements (Graham, 2001, p. 10).

There are two essential terms related to currency futures contracts. The first one is the currency spot rate, which is the current quoted rate of buying or selling a given currency in exchange for another currency. The currency spot rate concerns transactions that exchange currencies upon trade or shortly afterwards. Such currencies involved in the transaction are referred to as a pair. The second term is the currency futures rate, which involves a trade of currencies at a future date. Because futures rates are based on spot rate changes, the two values correspond with each other and change together. For instance, if the spot rate decreases, the futures rate and thus the price of a given currency pair will also decrease and vice versa. The level of impact is dependent on the future date of the transaction. The longer the date, the lesser the impact of the spot rate on the futures rate (Graham, 2001, pp. 11-12).

The requirement for currency futures contracts is for traders to have capital that can cover margins and losses brought about by taking the position. However, traders can exit their obligation to either purchase or sell a given currency before the expiration date. Like in other contracts, it is done by closing out the position (Graham, 2001, p. 13).

As for the price of foreign currency futures, it is determined by trade. Consider the following example. A company is purchasing a Euro FX future on the US exchange at 1.30 in euros. Therefore, the company takes the obligation to buy euros at $1.30. Based on the information acquired from the Chicago Mercantile Exchange, a single euro FX future is 150.000 euro; thus, the company has to buy at least one currency futures contract of that type.

Now, the mentioned company is based in the United States and wants to hedge against its projected receipt of 150 million euros in November. Before that time, the company is able to sell currency futures contracts. As it has already been mentioned, a single EURO FX futures contract comes to 150.000 euros. The amount to be received is in euros, which are not the currency of the United States. Because the company is operating in this country, it can sell the owned futures contracts on euros and lock in a rate of future exchange to US dollars. If the company sells 1000 futures contracts and each is 150.000 euro then,

$$150.000 \times 1000 = 150\,000\,000$$

The result is 150 million euro, which the company will receive in dollars at the agreed index price of $1.30 per euro. Thus,

$$15\,000\,000 \times 1.30 = \$19\,500\,000$$

The difference is

$$19\,500\,000 - 15\,000\,000 = \$4500\,000$$

Due to currency fluctuations, the company may have either gained profit or lost money during that transaction. For instance, if in November the current price of 1.30 dropped to 1.25, then,

$$15\,000\,000 \times 1.25 = 18\,750\,000$$

Hypothetically, the company would have received the following amount.

$$18\,750\,000 - 15\,000\,000 = 3\,750\,000$$

Now the difference between the current price of 1.30 and 1.25 is

$$4\,500\,000 - 3\,750\,000 = \$750\,000$$

Nevertheless, the company agreed to sell at the price of 1.30, so in relation to the current currency index, it gained a profit.

There are many different types of currency futures contracts available to traders. The most popular currency contracts are those between the US dollar and the euro. Such a contract is called the EUR/USD dollar currency futures contract. Other frequently traded pairs include the British Pound/U.S. dollar futures contract called GBP/USD and the British Pound/euro futures contract called GBP/EUR. The range of liquidity ranges significantly between different types of currency futures contracts. The most popular contract, the EUR/USD contract, might undergo as many as four thousand transactions each day, while contracts such as Brazilian real/U.S. dollar might cover mere thirty-three contracts (Graham, 2001, p. 14).

As for exchanges dealing in currency futures contracts, they are traded on exchanges with the ensured regulation of centralized pricing and clearing. In other words, the market price of a currency futures contract will be the same for all brokers (Graham, 2001, p. 15). The largest marketplace for currency futures is the Chicago Mercantile Exchange (Chicago Mercantile Exchange, 2020), which has 49 currency futures contracts in its offer, and their daily liquidity comes to more than one hundred billion US dollars.

Other important marketplaces are the Tokyo Financial Exchange (Tokyo Financial Exchange, n.d.), NYSE Euronext (NYSE Euronext, n.d.), and the Brazilian Mercantile and Futures Exchange (Brazilian Mercantile and Futures Exchange, n.d.).

1.4.2. Interest Rate transaction

Percentage transactions that take place on futures markets are called interest rate futures. This type of futures contract includes an underlying asset that comes with interest. Therefore, it can be described as a contract between two parties, the seller and the buyer, to deliver the asset with interests at a future date. As it can already be concluded, such future contracts make it possible for the buyer and the seller to lock in the price of the asset with interest to be sold at a future date (Kobold, 1986, pp. 20-25).

Different exchanges use different underlying assets in their transactions. For instance, Treasury bill, also known as T-note futures traded on the CME, uses treasury bills and the treasury bond futures contracts traded on the CBT, as the name suggests, use treasury bonds. The most popular interest rate futures are for 30-year, 10-year, five-year and two-year T-notes. The purpose of such futures is to hedge or speculate (Aikin, 2006, p. 250). Consider the following example using 10-year T-note (Aikin, 2006, p. 140):

The face value of the note $100,000, and each contract includes one of them, so the contract size is $100,000. Handles of $1,000 are used to trade such futures contracts, and one handle comes to thirty-two seconds, that is,

$$\$1{,}000 \div 32 = \$31.25$$

After that, to calculate the total price of such futures contract one has to take into consideration the quote, which is listed as 101-25 (Chicago Mercantile Exchange, 2020). Subsequently, the equation for the calculation of the total price should include face value, plus one handle, plus $\frac{25}{32}$ of another handle, that is,

$$\$1000{,}000 + \$1{,}000 + \left(\$1{,}000 \times \frac{25}{32}\right) = \$101{,}781.25$$

Therefore, the total value of a Treasury interest rate futures contract comes to $101.781.25

On the other hand, Eurodollar futures contracts differ from Treasury interest rate futures contracts in nearly all aspects. Contract size, in this case, comes to $1 million, handle size $2,500 and increments to $25. The minimum price movement of such a contract comes to a mere $6,25 because such contracts can be traded at values of half-tick and quarter-tick (Aikin, 2006, p. 151).

As for the price value of the interest rate, it moves in opposite directions to fluctuations of interest rates. It means that when the interest rates go up, the price value automatically goes down (Aikin, 2006, p. 152). If a trader engages in speculation and buys a 30-year old Treasury bond future for 102'28, that is $102,875, and after one year, the price comes to 104'05 ($104,156.25) due to the lower interest rates, his or her speculation came true. Thus,

$$\$104{,}156.26 - \$102{,}875 = \$1{,}281.25$$

The trader, by his or her speculation, made a profit of 1,281.25 dollars.

One particular type of interest rate futures is STIR, a short-term interest rate future. It is a type of contract, which takes its value from the interest rate at its maturation. The following are common STIRs (Aikin, 2006, p. 30):

- Eurodollar,
- Euribor,
- Euroyen,
- Short Sterling,
- Euroswisss.

It is difficult to unanimously classify STIRs because they tend to vary from one contract to another, but their interest rate index is defined as 3-month sterling or US dollar LIBOR (London Interbank-Offered Rate).

STIRs are traded in a broad range of currencies. The following table lists representative contracts in respect to their country (Aikin, 2006, p. 31).

Table 1.6: A list of representative contracts.

Country/Region	**Short-term interest rate future**	**Exchange that trades in the described STIRs**
United States of America	90-day Eurodollar 1 month LIBOR	International Monetary Market for the Chicago Mercantile Exchange.

	Fed Funds 30 day	The Chicago Board of Trade
Europe	3 Months Euribor 90-day Sterling LIBOR Euro Sfr	Euronext.liffe
Asia	3 months Euroyen 90-day Bank Bill BB3	Tokyo Commodity Exchange, Sydney futures exchange

1.4.3. Index transaction

Another type of the futures contract is called index transaction, which in the case of futures are called index futures. Every index is marked with a different multiple that is used to calculate the price of a given futures contract. For example, based on the acquired data, the S&P 500 Index is among the most traded index futures contracts in the USA (Dorman Trading, n.d.).

The basic principle of an index futures contract is that a trader agrees to buy an index at an agreed-upon price on a specified future date. If the index price is higher than the agreed-upon price, the trader has gained profit, and the selling party suffers a loss. Now, let us consider the opposite situation, in which it is the buyer who made a profit because the agreed-upon price was higher than the index price on the day of the transaction. Price fluctuations occur until the contract expiration date; thus, the trade must have enough funds to cover potential losses (Sutcliffe, 2018, p. 10). This margin has already been described as the maintenance margin.

As the name suggests, index futures are based on an underlying asset. In such futures transactions, it is impossible to trade the asset directly. It is easy to explain the example of the S&P 500 index. For instance, the index of gold stock tracks movements of all stocks that are related to Gold, the S&P 500 index is tasked with tracking price movements of stocks traded by the 500 largest companies in the United States of America. In order to match such an index, a given trader would have to purchase five hundred different stocks. Index futures are traded the same way other futures are traded on the related markets (Sutcliffe, 2018, p. 4).

Index futures are mostly used for hedging; however, there are several disadvantages of such operations. However, let us consider that a trader buys many stocks, but they can hedge their exposure after selling the owned index futures. Index futures contracts may gain value if the owned stock falls in value. Therefore, the trader can offset the loss of his or her stocks. Now, let us imagine that hedging was not really required, and the market is still rising. In such a situation, the trader would generate a loss and reduce his or her profits (Figlewski, 1983, pp. 20-26).

Another use of index futures contracts is to speculate. A trader can buy a whole group of assets by engaging in index future transactions. The price determinant is entering and exiting the contract (Figlewski, 1983, pp. 27-28). Consider the following example:

Value of a tick of the S&P 500 index future: $250

Index value: assumed 2000

$$\$250 \times 2000 = \$500{,}000$$

Value of one index futures contract: $500,000

Due to the value of the S&P index future, if the index value falls from 2000 to, for instance, 1800, then the contract would be worth $450,000, and the trader would generate a $50,00 loss, but if the index value rises to 2100, the contract would be worth $525,000. However, it is not required for the trader to cover the contract's total value, in this case, $500,000, when entering it. The requirement is to possess some percentage of the contract value in one's account. The initial margin, which has already been described in the previous parts of this chapter.

Some of the popular index futures used in the United States of America are based on equities. Such futures include:

- E-Mini S&P 500 (ES),
- E-Mini NASDAQ 100 (NQ),
- E-Mini Dow (YM).

There is a strong correlation between index futures and the underlying indexes, but there are also specific differences between the two. If an investor buys long contracts on the stock in the index, there are no receiving dividends, and in the case of short contracts, there are no owing dividends. Like all futures contracts, index futures are also based on margins. For instance, if a trader buys contracts worth $200,00, he or she has to outset 5% of the principal amount, that is $10,000. However, when trading in the stock components or shares of Exchange Traded Funds (ETF), the trader has to outlay the total value of $100.000. As for the relation between the index futures price and the underlying index value has to be equal only upon the contract's expiration date. The fair value of an index futures contract is relative to the index, which reflects deductions from the index values, that is, the expected dividends as well as costs of financing the difference between the initial margin and the principal amount of the contract between the date of trade and the expiration date of the contract (Figlewski, 1983, p. 29).

The trading hours of index futures regulate and arbitrate the fair value of such contracts, however, on the condition that the underlying stocks and index futures are traded simultaneously. Brick and mortar stock markets in the United States open at 9.30 a.m. Eastern Time and close at 4 p.m. Eastern Time, but it is possible to trade index futures online, where digital platforms work 24/7. An example of such a system can be Globex, a trading system operated by the Chicago Mercantile Exchange Group. Outside trading hours of brick and mortar stock exchanges, the liquidity of index futures drops because part of the market cannot take part in transactions, which occur outside of the market (Figlewski, 1983, p. 30).

1.4.4. Commodity transaction

A commodity transaction, also known as a commodity futures contract, is an agreement entered into between two parties related to purchasing or selling an agreed-upon amount of a given commodity at a specific price and on a specific day after entering into the agreement. The primary purpose of such a transaction is to avoid the risk resulting from price fluctuations of raw materials or other underlying products that are the subject of a futures contract. Moreover, it is also a good and convenient way for sellers to secure guaranteed prices (IBP Inc., 2016, p. 24).

Commodity transactions and the associated commodities futures contracts, are mostly used to influence price directions of raw materials. However, this type of futures requires experience and according to the literature should be avoided by beginners. The main risk brought about by commodity futures is the high amount of leverage associated with holding futures contracts (IBP Inc., 2016, p. 25). Consider the following example:

§The initial margin is set at \$6,000, and an investor enters into a futures contract for 1,000 barrels of oil, thus

$$\$60 \times 1{,}000 = \$60{,}000$$

The total value of oil barrels comes to \$60,000, and the value of one barrel is \$60.

Such a transaction involves a large amount of leverage, and even a very small move in the commodity could result in either a significant loss or gain when compared to the value of the initial margin (IBP Inc., 2016, p. 26).

The type of a contract requires the buyer or the seller to accept the underlying asset based on an obligation. Therefore, if an inexperienced investor does not close an existing position, he or she may accept a delivery of commodities he does not want or cannot sell (IBP Inc., 2016, p. 27).

Another use for commodity transactions is associated with locking in the selling or buying price in advance, expressed in weeks, month, or even years. Consider the following example:

A farmer expects to produce 1,000,000 bushels of soybeans in the coming year. On American markets, a typical size of such a futures contract comes to 5000 bushels. Assuming that the break-even point for each bushel comes to $10 per bushel, and the prices in the current year of a futures contract comes to $15 per bushel, thus,

$$1\ 000\ 000 \div 5000 = 200$$

gives 200 contracts per year.

If the farmer sells 200 contracts at a price of $15, then he will sell out all soybeans from his harvest.

The following year, the farmer receives his money for the sold 1.000.000 bushels of soybeans, thus

$$\$15 \times 200 = \$3000$$

which has to be multiplied by 5000 bushels contained in each commodity futures contract.

$$5000 \times \$3000 = \$15\ 000\ 000$$

That is locked in the price.

However, if the price of soybean is lower than on the day of entering into the futures contract, for instance, \$12 per bushel, the farmer receives a \$3 benefit per every bushel due to hedging (the break-even point for each bushel came to \$10), or in other words a \$3,000,000 profit, because,

$$\$3 \times 1{,}000{,}000 = \$3{,}000{,}000$$

If, however, the price came to, for instance, \$18 per bushel, the farmer missed out on a \$2, and \$2,000,000 in total, of additional profit (IBP Inc., 2016, p. 30) that is,

$$\$2 \times 1{,}000{,}000 = \$2{,}000{,}000$$

Commodity transactions concern many raw materials such as oil, metals and food. Prices of all commodities are determined by different factors. When dealing with commodity transactions related to oil, traders consider all information about supply and demand as well as geopolitical conditions. These three factors have a great impact on oil prices. Moreover, those assumptions influence the whole economy, because every good and service produced in America depends on oil prices. In 2008, oil prices soared despite global demand going down and supply up (Singleton, 2011, pp. 1-2).

According to the Energy Information Administration, oil consumption went down from 86.66 million barrels per day in the last quarter of 2007 to 85.73 million barrels per day in the second quarter of the following year. At the same time, during this period supply increased to 85.49 million barrels per day to 86.17 million. This contradicts basic laws of supply and demand which postulate that in such situations prices should go down, and not up. As a result, prices rose 24% by the end of May (Singleton, 2011, p. 3).

According to the conclusions drawn by Singleton K.J., who in his research *Investor Flows and the 2008 Boom/Bust in Oil Prices* analyzed the above-mentioned situation, such situation was caused by the flow of investment money that came into commodity markets that year. Money from real estate and stocks were withdrawn and invested into oil futures. The same year, prices of oil went up to the shocking \$145 per barrel, the highest amount to date (Singleton, 2011, p. 6).

As mentioned earlier, oil is one of the main commodities traded in the USA. As an example of its influence, consider the following events from recent years. In 2011, oil prices went up in May, and thus gas prices also went up immediately because oil comes to 72 per cent of gas prices (The US Energy Information Administration, 2012).

The following year, Iran made some threats to close the Strait of Hormuz, which is one of the most important oil shipping lanes in the world. Again, oil prices went up because trades were afraid that the closing would limit oil supply. The increase occurred in April, and following month gas prices also went up (The US Energy Information Administration, 2013).

At the beginning of 2013, Iran again made some threats related to the Strait of Hormuz, and trades again bid up oil prices. According to data, oil prices in February came to $118.90 per barrel and gas prices $3.85 by the end of the same month (the US Energy Information Administration, 2014).

Another important group of commodities that can be traded using Futures contracts are metals, both precious and industrial such as Gold, silver and copper. The number of Gold futures contracts often goes up in uncertain times, as traders consider them to be a safe haven. For instance, Gold in 2011 achieved an all-time high of $1.895 per ounce prior to 2020. This situation was not caused by demand and supply but rather by traders who increased gold prices as a response to the uncertain economic situation (Yusuf, 2011). Following the activity of Gold futures makes it is possible to better comprehend the state of the economy because increased gold inflows drive up gold prices, which could mean that the economy is doing poorly. On the other hand, decreasing gold prices is crucial for obtaining profits from other sources and reinforcing the economy (Amadeo, 2018).

Some of the factors that influence values of metals futures contracts include currency indexes as well as supply and demand. For instance, in 2015, the economy of China started to progressively slow down, receding its demand for copper. Economic reforms introduced in the country at that time saw a shift from construction to consumer spending. China started to develop its own system in order to become more independent and substitute exports with domestic demand. That shift enabled China to add to the supply of commodities, for instance aluminum, what lowered prices all over the world. From 52 percent of the global aluminum supply, China came to 62 per cent in the following year (Bloomberg BusinessWeek, 2015).

The next category to be discussed here includes food and grain commodities, which are renewable on a seasonal basis. Food includes coffee, cotton, sugar and cocoa. The factors at play here include disease, infestation caused by insects and droughts. Moreover, a significant portion of the food market includes grains, and the most popular are soybeans and oilseeds, which are irreplaceable in food production and supply. As it has already been mentioned, drought is one of the main influential factors that condition harvests; however, other weather effects such as heavy rains or extreme temperatures have to be taken into consideration as well (CME Group, n.d.).

Livestock is the last category and encompasses feeder, cattle, lean hogs and pork bellies. These commodities are also renewable and are driven by the demand and supply and prices of grain commodities used in feeding processes. All of the above commodities are traded on one market, CME Group Inc. The main factors that affect these types of commodities include consumer demand, feed prices, animals born and sold to the market, and natural factors such as disease and the weather (CME Group, n.d.).

The commodity futures market is regulated by an independent agency of the US government. The US Commodity Futures Trading Commission. It was created in 1975 and currently regulates both futures and options markets. According to the Commodities Exchange Act, the agency is tasked with fostering an open, transparent, competitive and financially sound market in order to avoid systemic risk. Moreover, one of its main aims is to protect the users of the market as well as their funds, consumers and the public against fraud, manipulation and abusive practices connected with different products, such as derivatives, which are subject to the Commodity Exchange Act (US Commodity Futures Trading Commission, n.d.).

Investments in derivative instruments carry significantly higher returns as well as risks when compared to investments in underlying commodities or Exchange Traded Funds (ETFs) that invest in the same commodity.

For example, an investor with $11,000 may invest it in ETF such as SPDR Gold Shares or Direxion Daily Gold Miners Index Bull 2X (Direxion, 2021), which would represent 5.5 ounces of Gold in the first ETF or 11 ounces of Gold in the second. Alternatively, the same investor can purchase a Gold future contract for $2,000 with an additional $9,000 outlay to cover margin requirement and have an investment in 100 ounces of Gold. That represents 10-20 times leverage when comparing investments with future contracts that deliver significantly higher risk and return opportunities.

2. FORECAST PRICES AND ECONOMIC FORECASTING

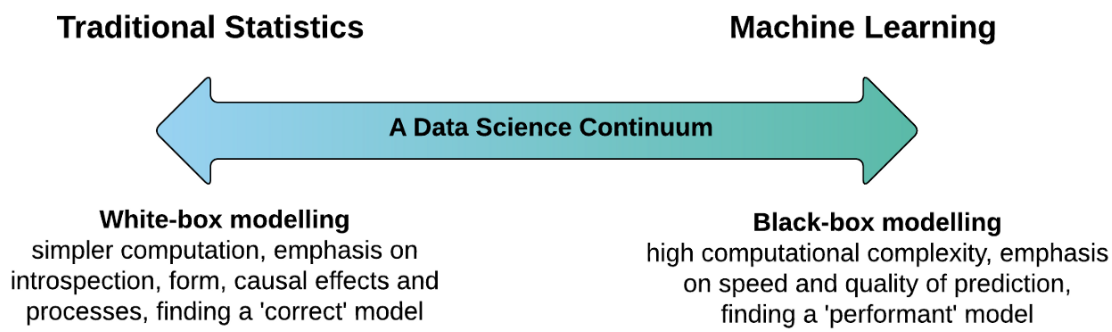
2.1. Quantitative and qualitative forecasting

It is essential to define the term forecasting before discussing the topic of quantification and qualitative calculations. According to the Oxford Dictionary, forecasting is "a calculation or estimate of future events, especially coming weather or a financial trend (Oxford Living Dictionaries of English, n.d.)." In economics, forecasting can be described as predicting the future based on past and present data on the way of analysis of current trends. In the case of futures contracts, forecasting mainly deals with estimating the profitability and chances of gaining profit or incurring losses. For instance, it can bean estimation relating to some variable amounts at some specified future date. Forecasting is somewhat similar to predicting, but the latter is a more general term. The process of calculating and estimating future amounts is related to statistical methods that take advantage of time series and data, both cross-sectional and longitudinal (French, 2017).

Two main factors come into play when it comes to forecasting, risk and uncertainty. It has been generally accepted as a good practice to define the level of uncertainty when forecasting. The most basic requirement for forecasting to be as precise as possible is to provide the latest data; that is, it must be updated before calculating some future values. However, it is also possible for data to be the subject of forecasting when predicting the variable of interest (Ellis, 2008, p. 10).

It is also essential to distinguish predictive models by the way independent variables are being treated and interpreted as well as *explainability* of the model (Hulstaert, 2019).

Figure 2.1: Data Science Continuum



According to Hulstaert (Hulstaert, 2019; Hall, et al., 2021), relatively recent Artificial Intelligence (AI) and Machine Learning (ML) algorithms differ from traditional statistical models in the way of capturing and understanding the causal effects. Traditional regression techniques provide an opportunity for variable selection by understanding variable importance, which can be easily quantified. They are typically referred to as White-box models. On the other hand, ML algorithms perform highly complex calculations of interactions of dependent variables, trying to optimize the predictive power of the model, which is often called a Black-box.

There are techniques available to provide some insights into how ML models work and provide interpretability of the inputs (Hall, et al., 2021). They provide some understanding of the importance of the variables and features of the algorithms, and when applied to ML models, such application changes classification of Black-box models to so-called Grey-box, or models where interpretability exists but not on the same level as with White-box models.

Some models, such as state-space, are Grey-box by their nature. That is because independent variables can be selected, and their importance can be understood in relation to the model's predictive power. However, the model utilizes a Markov Chain type of algorithm to determine coefficients of the space part, and that process cannot be easily understood or interpreted.

Traditionally, White-box models were preferred by institutional and individual investors due to their interpretability and relative ease of application. More recently, ML Black-box models gained popularity with institutional investors, who can afford to hire professionals in the field. It is often cited that Black-box and Grey-Box model outperform their White-box counterparts; however, most of the models are proprietary and are operated by large institutions that have no incentives to make them public.

2.1.1 Application of forecasts

Forecasts find their application in many fields, in which it is necessary to know how future conditions are going to change and to what degree. It is acknowledged that in economics, not everything can be reliably forecasted. If factors that come into play are well known and there is enough data, the forecast can be reliable (Ellis, 2008, p. 12). The following forecasting applications show their degree of use in various fields of science, everyday life and economics.

- Supply chain management
- Economic forecasting
- Earthquake forecasting
- Egain forecasting
- Finance against risk based on credit ratings and credit scores
- Land use
- Sports performance
- Product
- Sales
- Technology
- Telecommunications
- Transportation
- Weather and Meteorology

The forecasting method known as eGain forecasting has become popular due to climate changes and increasing energy prices. This type of forecasting aids in calculating how much heat is needed to heat a building (Ellis, 2008, p. 12). Another type is called Customer Demand Planning and is used by companies that manufacture and distribute products (Murphy, 1999, p. 60).

Many companies, both non-profit and for-profit, deal in providing analysis based on forecasting economic trends. This action is widespread for actual stock returns. As for forecasting movements of foreign currency, it is mainly carried out based on charts and fundamental analysis. This type of analysis deals with financial statements, such as assets, liabilities and earnings, health, competitors and markets. However, it does not limit itself to those features because it also considers the general state of the economy while analyzing interest rates, production, earnings, GDP, manufacturing, employment and housing. Fundamental analysis can be performed either bottom-up or top-down. The terminology is used to distinguish it from other investment analyses like quantitative and technical analyses (Murphy, 1999, p. 61). The application of fundamental analysis is found in the financial forecast, where it handles historical and present data. The primary goals of a fundamental analysis include (Kowalski, 2021):

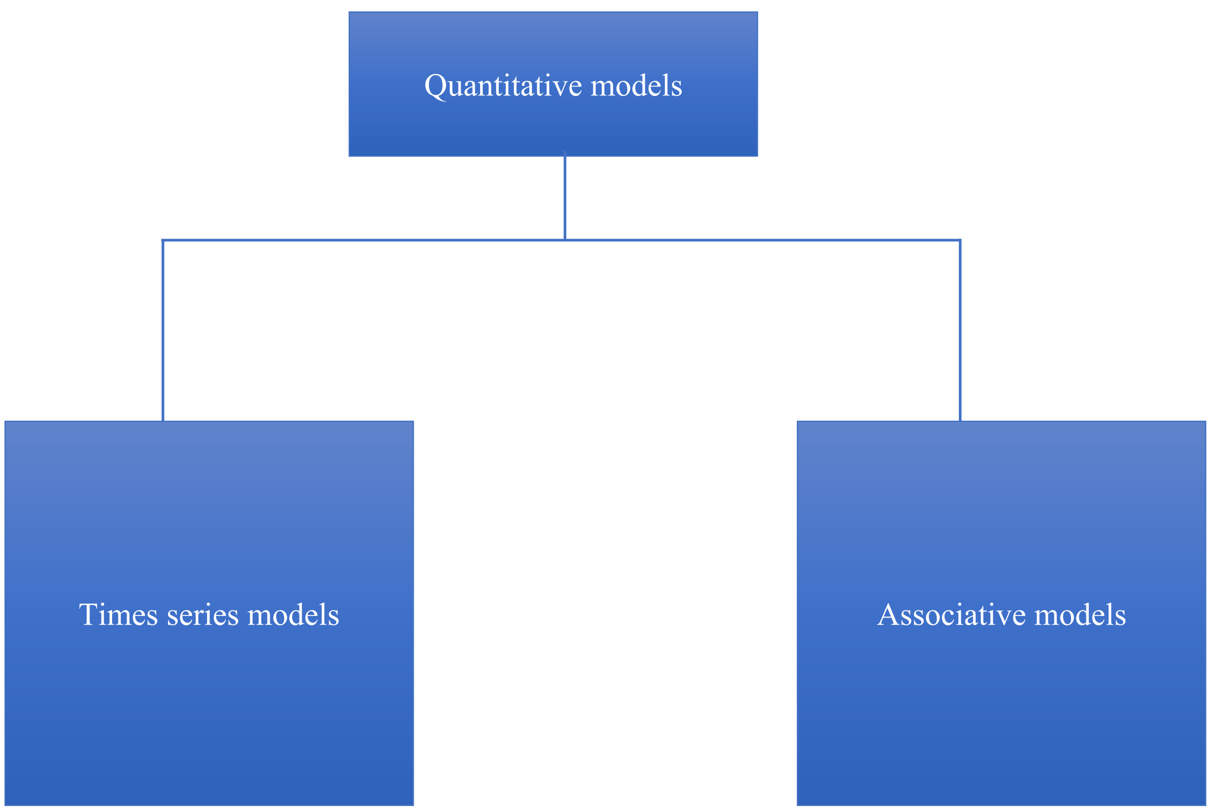
- stock valuation of a company with predation of future price evolution,
- projection of the company's business performance,
- evaluation of management and internal business decisions,
- calculation of the company's credit risk
- demand for commodities at different price levels
- supply of commodities and ability to meet the increase in demand
- reproducibility of agricultural commodities due to climate factors
- changes in demand and supply due to changes in related external factors such as technology
- changes in investment strategies due to changes in monetary policy

Typically, prices fluctuate significantly in the short term, making a fundamental forecast for short term trades very difficult with a high risk of overfitting when using statistical models. The longer-term trends are easier to spot for fundamental analysis, but leveraged investing is more difficult due to risks of high short-term losses when using futures and significant premiums asked by market makers in options markets.

When it comes to methods used in forecasting, there are two main categories of techniques. The first one is qualitative forecasting, which is subjective and based on information acquired from consumers and experts. Their use is justified and correct when there is no solid and reliable past data that can be used in the process of forecasting (Murphy, 1999, pp. 62-63).

Qualitative methods are mostly used in long-term decisions; on the other hand, quantitative forecasting is used to predict future data, which serve as a function of past data. Their use is appropriate in situations where past data consisting of numbers are readily available, and it is safe to assume that some of the patterns that can be found while analyzing the data are expected to continue into the future. Contrary to qualitative models, quantitative forecasting is mainly applied to short-term decisions (Armstrong, 2001, p. 12). The following chart depicts two of the most popular quantitative models.

Figure 2.2: Models of quantitative forecasting.



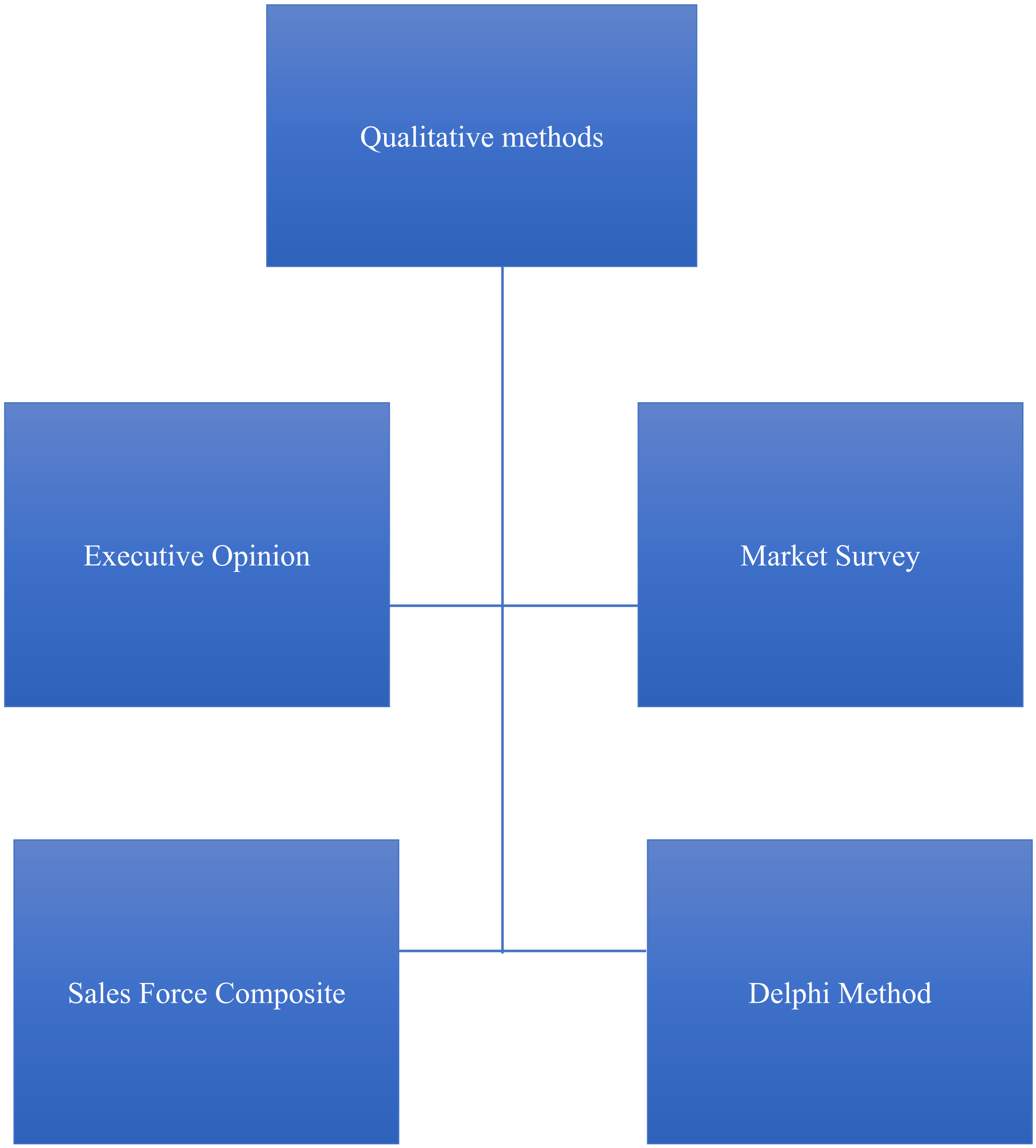
The first type of models analyses past data patterns and makes predictions of the future based on those patterns, which are obtained after analyzing past data. The second type, also referred to as casual models, assume that the variable under forecast is connected to other variables found in its environment. A forecast of this type is made on the basis of such associations between variables. The following table lists some of the most popular time series models, some of which are described in length in the third part of this chapter (Armstrong, 2001, p. 13) (Kress & Snyder, 1994).

Table 2.1: Models of quantitative forecasting.

Model	**Description**
Naive	The actual value of the last period is used for forecasting.
Simple Mean	Forecast on the basis of an average of all data from the past
Simple Moving Average	Limited and selected number of most recent data sets, each data is of the same importance (weight)

Weighted Moving Average	Limited and selected number of most recent data sets, each data is of different levels of importance (weight)
Exponential Smoothing	A procedure based on average values which are weighted in a way from top to bottom (older data has lesser weight)
Trend Projection	Based on the least-squares method, which tries to adjust a straight line to the data
Seasonal Indexes	Based on adjusting the forecast to seasonal patterns found in the analyzed data

Figure 2.3: Methods of qualitative forecasting.



The executive opinion is based on a meeting of managers who create a collective forecast based on their knowledge. Market Survey uses tools such as interviews and surveys to determine customer preferences and forecast demand. The Delphi Method is based on the formation of an agreement between various experts collaborating on a given venture. Last but not least, Sales Force

Composite is a method developed for individual regions in which each seller or distributor evaluates sales based on the available data (Kress & Snyder, 1994, p. 89).

2.1.2 Neural Networks

According to research carried out by experts, the implementation of different methods may lead to different degrees of accuracy of forecasts. For example, it is possible to state that GMDH neural network performs better in forecasting some classical algorithms (Kress & Snyder, 1994, p. 90).

GMDH stands for group method of data handling, and it is a group of inductive algorithms of mathematical modeling based on computer calculations of multi-parametric datasets. It is distinguished by a fully automatic structural and parametric optimization of models. The main areas of implementation include data mining, knowledge discovery, forecasting and pattern recognition (Armstrong, 2001, p. 24).

GMDH algorithms have an inductive procedure that sorts out complicated models gradually by selecting the best solutions out of polynomial models through external criteria. An example of a GMDH model with multiple inputs and only one output is presented below (Armstrong, 2001, p. 25):

$$\boldsymbol{Y(x_1, \dots \dots \dots . x_n) = a_0 + \sum_{i=1}^{m} a_i f_i}$$

where

$\boldsymbol{f}$ is elementary functions that depend on different sets of inputs

$\boldsymbol{a}$ stands for coefficients

$\boldsymbol{m}$ is the number of base function components

In order to find the best possible solution, the group method of data handling uses various subsets of components of the base function, which are referred to as partial models. The least-squares method is used to determine the coefficients of such models. Algorithms implemented in GMDH increase the number of martial models and define a structure that can be used for optimal complexity, which is set by the minimum value of an external criterion. The whole process has been named the self-organization of models. The following model is the most popular one, and it is the gradually complicated Kolmogorov-Gabor polynomial (Kress & Snyder, 1994, p. 92).

All forecasting methodologies have some limitations. As it has already been mentioned, the more data is available, the more reliable a forecast can or should be. It assumes the causality between dependent and independent variables and the absence of randomness. Sometimes data may capture random events that do not have any relation to a variable that is being predicted; for example, it is impossible to predict the results of the lottery or a dice roll even though historical data is available. It is often the case in stock and foreign exchange markets that not all data and other factors are known; thus, forecasts frequently turn out to be inaccurate or plain wrong. It is like a chain reaction because an incorrect forecast affects everything connected with it on the market, and the behaviour of investors also changes, thus reducing the forecast even further (Kress & Snyder, 1994, p. 93).

2.1.3 Accuracy of predictions

A very significant factor in forecasting is its accuracy. The so-called forecast error is expressed as the difference between the two values, the real and forecasted. The two values need to have a corresponding common period. The basic equation used to calculate the error is presented on the next page (Rescher, 1998, p. 67).

$$\boldsymbol{E_t = Y_t - F_t}$$

where

$\boldsymbol{E_t}$ forecast error during period $\boldsymbol{t}$

$\boldsymbol{Y_t}$ actual value of period $\boldsymbol{t}$

$\boldsymbol{F_t}$ forecast value of period $\boldsymbol{t}$

Every forecasting method that has been used efficiently will produce residuals, which are not linked. If there is a correlation between values of residuals, they should be considered because the information contained in them may be of use when estimating forecasts and developing them. In order to do that, the expected value of a residual has to be calculated as a function of the known past residuals. Subsequently, the forecast has to be altered by the expected value's difference from zero. Another component of a useful foresting method is the zero mean. If the mean between residuals is other than zero, the forecasts will not be accurate, and in order to improve them, the researcher has to his or her change the forecasting technique.

There are various types of errors (E); the main ones are described below (Rescher, 1998, pp. 68-78).

- Scaled Error. The forecast error is on the same scale as the data. It is not possible to compare different series because of the scale difference. Examples of scaled errors include:

✓ Mean Absolute Error calculated from the equation

$$\boldsymbol{MAE = \frac{\sum_{t=1}^{N} |E_t|}{N}}$$

- ✓ Mean squared error calculated from the equation

$$MSE = \frac{\sum_{t=1}^{N} E_t^2}{N}$$

- ✓ Root mean squared error calculated from the equation.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} E_t^2}{N}}$$

- ✓ Average of Errors

$$\overline{E} = \frac{\sum_{t=1}^{N} E_t^2}{N}$$

- Percentage Error. Such errors are primarily used to compare performances of forecasts between various data sets because, unlike scaled errors, these do not depend on the scale. Their main disadvantage is their size, then Y is close to zero or equal to it.

- ✓ Mean absolute percentage error

$$MAPE = 100 * \frac{\sum_{t=1}^{N} \left|\frac{E_t}{Y_t}\right|}{N}$$

- ✓ Mean absolute percentage deviation

$$\boldsymbol{MAPD} = \frac{\sum_{t=1}^{N}|E_t|}{\sum_{t=1}^{N}|Y_t|}$$

It has previously been stated that scaled errors cannot be used for different series of data. However, in 2006 Hyndman and Koehler (Hyndman & Koehler, 2006, pp. 679-688) proposed their use as an alternative for percentage errors. The mean absolute scaled error can be calculated from the following equation.

$$\boldsymbol{MASE} = \frac{\sum_{t=1}^{N}\left|\frac{E_t}{\frac{1}{N-m}\sum_{t=m+1}^{N}|Y_t - Y_{t-m}|}\right|}{N}$$

where

$\boldsymbol{m}$ stands for the seasonal period or equals 1 if the forecast is non-seasonal.

Business forecasters and practitioners frequently use different terminology to refer to the calculations mentioned above; for instance, the MAPE is often called PMAD. When selecting the forecasting method for a specific data set, its accuracy is based on the error mentioned above. The method that generates the lowest error is selected as the preferable one in most scenarios (Rescher, 1998, p. 87). That, however, may be different when forecasting a regime change is more important than the accuracy of individual time point predictions.

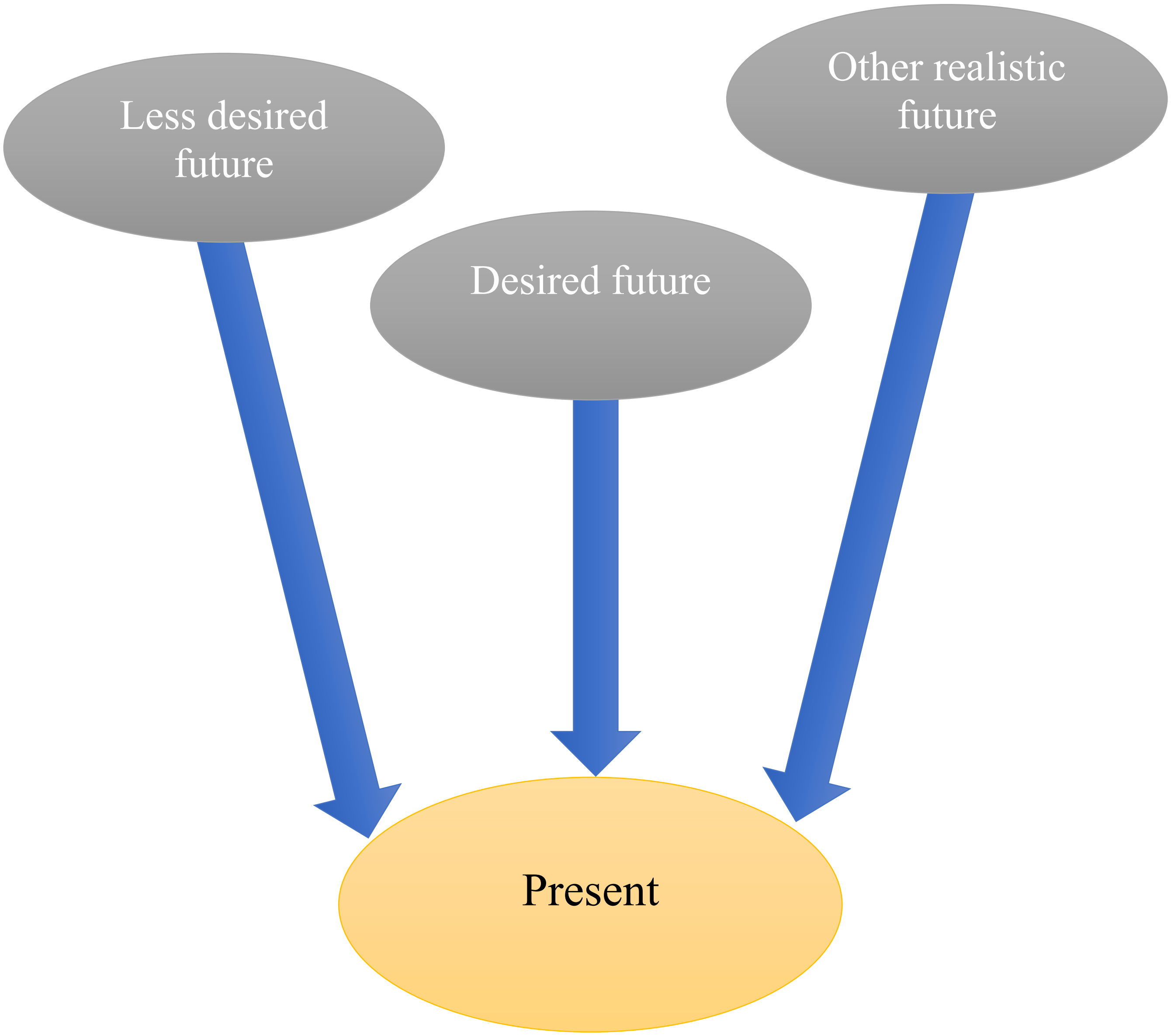
2.2. Types of forecasts

The division of forecasts is based on their nature and application. Two main types are exploratory and normative, which can further be split into quantitative and qualitative methods. The two have already been described in the first subchapter of the thesis at hand; however, they include many different techniques that have to be elaborated on. Both normative and exploratory types of forecasts may employ the same techniques; however, the difference between the two comes down to differences in the approach. Both types have been described on the following pages of this chapter.

2.2.1 Normative methods

One of the most popular types includes normative methods. In the beginning, a preliminary depiction of a desirable and possible future is created, which concerns a particular interest. From this point onwards, the analyst works backwards to see how and if those desired futures can develop from the present. Points, which are considered, include the degree of achievement, avoidance, existing constraints, available resources and technologies. The chart below depicts a normative type of forecast (Geisser, 1993, p. 23).

Figure 2.4: Normative forecasts.



Each type of methodology employs its own techniques used to carry out the forecast. In the case of the normative approach, such techniques include morphological analyses, relevance trees, and models like the Delphi model. Moreover, researchers have started to use success scenarios in recent years, and there are also many workshops available that relate to the normative type called aspirational scenarios. In those scenarios, participants establish a version of a future together, which is as desirable as it is credible, and try to find ways to achieve such a future (Geisser, 1993, p. 24).

2.2.2 Exploratory forecasts

On the other hand, there are exploratory forecasts, which differ from normative forecasts due to their nature and the implemented approach. Instead of starting with the future, the type at hand begins this process with the present, and gradually moves towards the future by asking “what if?” questions and extrapolating past trends. It is common knowledge that most studies that revolve around forecasting are of exploratory nature. The following model presents the basic scheme of an exploratory forecast.

As has already been mentioned, quantitative methods differ from qualitative due to their nature and the way of application. According to Theodore Jay Gordon, they can be described as,

"(…) the land of visionaries who can express their hopes in terms of numbers, such as a chief executive officer setting production goals for his or her company. (…) the home of analysts, comfortable with mathematically based methods, which use equations to arrive at their conclusion about what the future might be (Gordon, 1992, p. 27).”

On the other hand, we have qualitative methods, which Gordon has described as non-numeric methods used by visionaries like Marx or Thoreau, and those who predict the evolution of future events using qualitative methods instead of quantitative ones. Such experts include Marshal McLuhan or Daniel Bell.

Figure 2.5: Exploratory forecasts (Geisser, 1993).

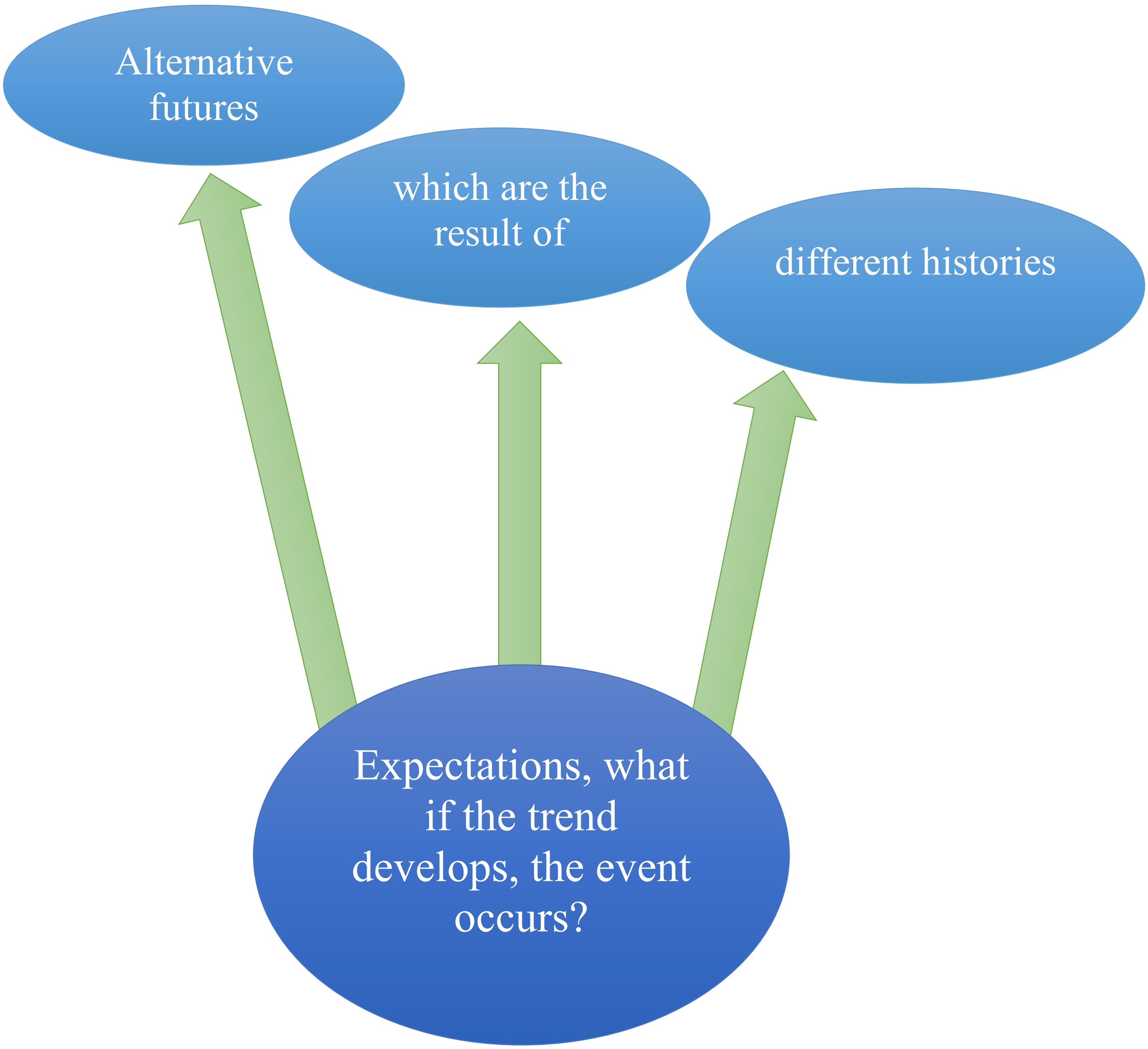


Figure 2.6: Types of quantitative forecasts (Gordon, 1992).

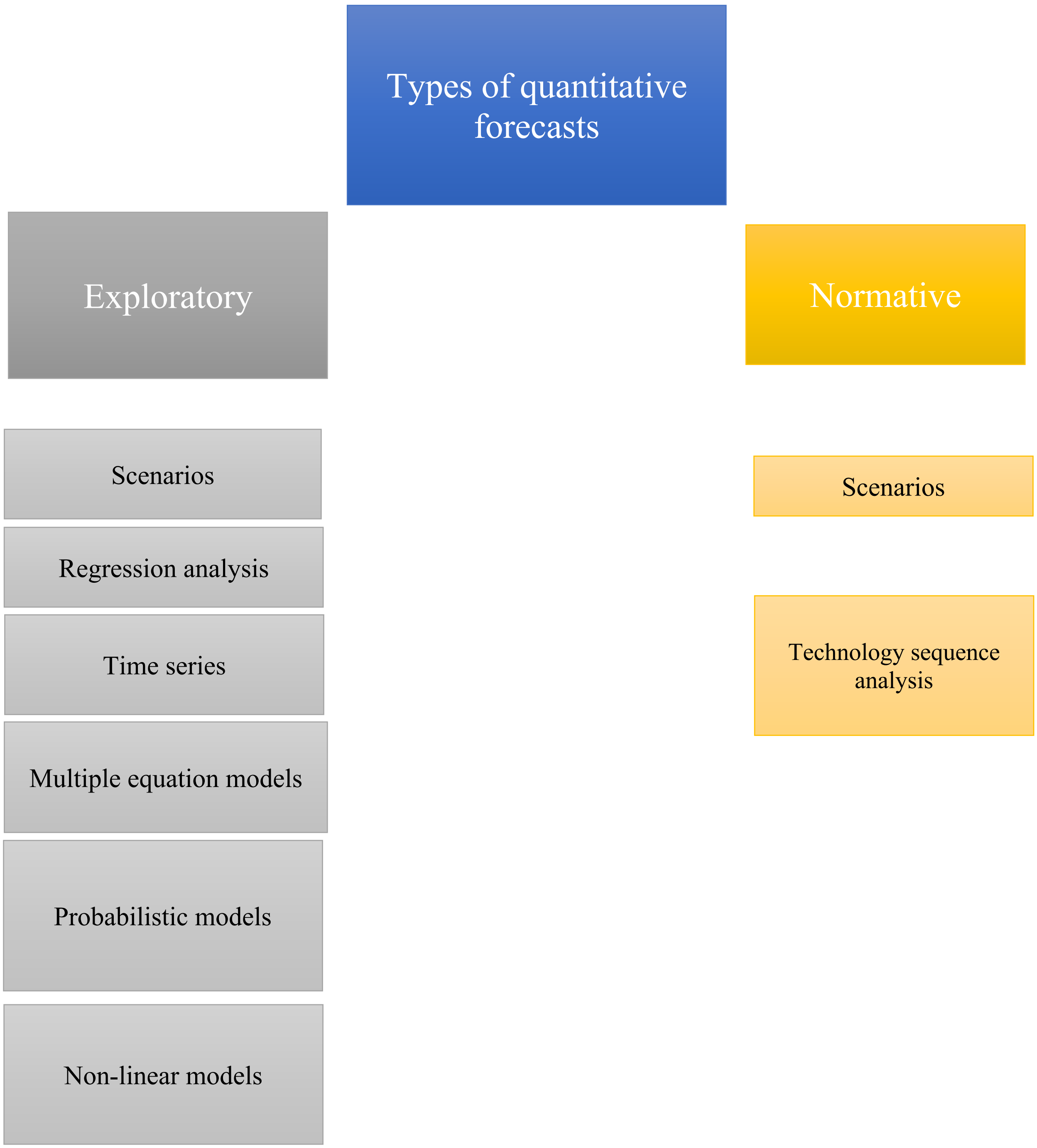
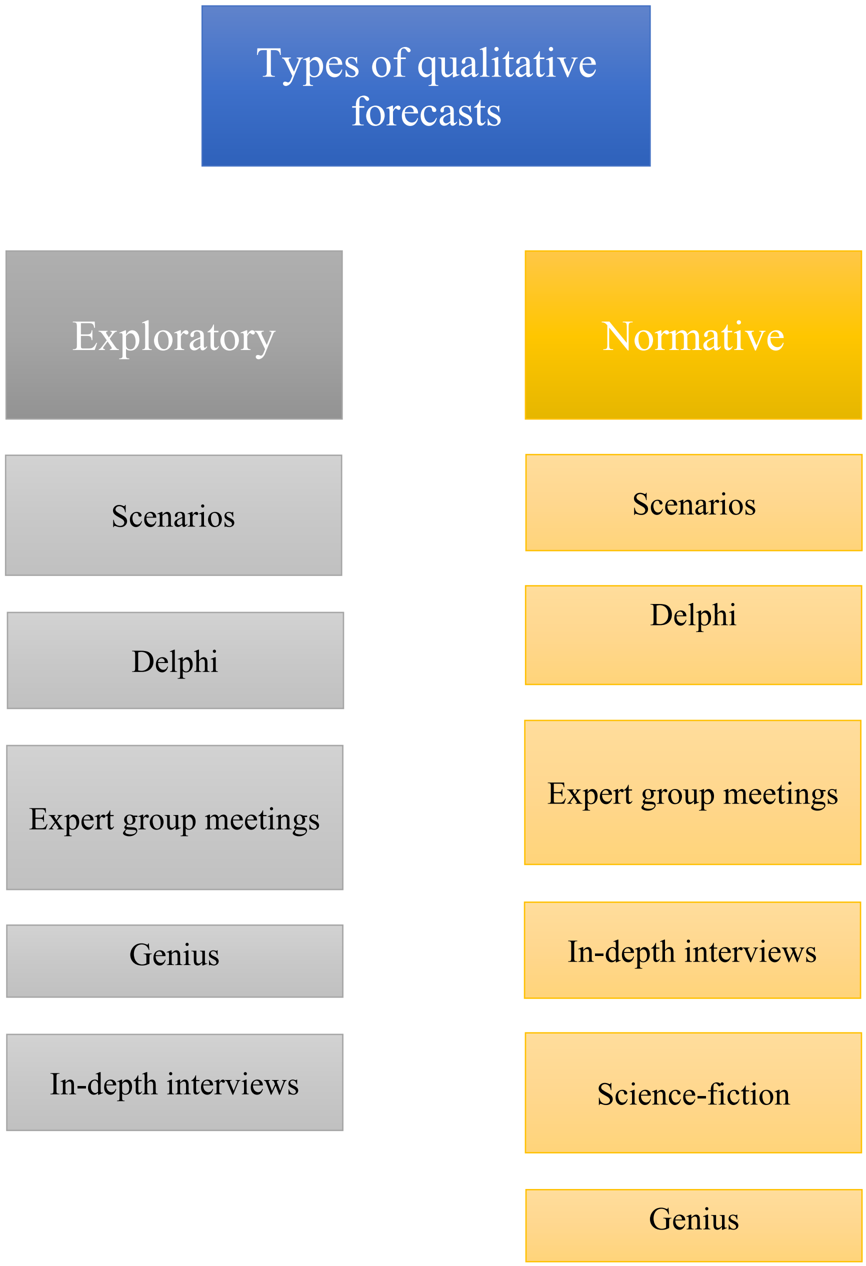


Figure 2.7. Types of qualitative forecasts (Gordon, 1992).



The first method implemented both by normative and exploratory types is genius forecasting. This method revolves around one person, who is the genius, integrating various factors that impact present circumstances and events to forecast the future. This person needs to have appropriate skills in order to present to others his image of the future events and how they are to be brought about. The method is not a formal one, and the only requirement for it to be effective is to possess the key features for its development, a genius (Gordon, 1992, p. 28).

2.2.3 Delphi method

The following method to be discussed is the Delphi method. Its beginnings date back to 1960, when research at RAND in California started to implement it. At that time, forecasts mostly revolved around military applications, potential and the development of technology that could be used in combat. The basic requirement for this method to work is to gather a group of experts who develop their opinion or statement together. It is based on the opinion of specialists because, according to the rule of this method, a group of experts are less likely to be wrong about future developments in a given field than a group of non-experts. The process of the Delphi method is quite simple. Each expert is given the same inquiries, which have to be anonymously answered. Statements are then gathered and analyzed, opinions that differ to a significant degree have to be justified and corrected in the group consensus view. Generally, the Delphi method cannot represent a significant number of the population's opinions, but it is all about the idea and its development (Gordon, 1992, p. 29).

The extrapolation of trends is based on analyzing a system and identifying the direction it is heading. This method is all about the momentum that carries the trend towards its limit. An important rule here is to remember that the forces in motion shall continue to move forward (Gordon, 1992, p. 30).

A time-series analysis implements mathematical methods that correlate with the trend data using either simple or complex techniques (Gordon, 1992, p. 31). The simple one is based on placing a curve on a series of historical data, which aim is to minimize the error between the placed curve and the data (Gordon, 1992, p. 30).

As mentioned earlier, both qualitative and quantitative methods of forecasting rely on modeling, scenarios and probability. The first one assumes that values of variables at different moments in the future can be dependent on factors other than time. For instance, the gasoline market is based not only on travel duration but also on miles driven, the number of vehicles in use, and engines' efficiency. Based on those variables and factors that come into play, different models that correspond to a given forecast are developed to be as accurate and efficient as possible (Gordon, 1992, p. 31).

On the other hand, scenarios are not as reliable as models because their main feature is to provide foundations for planning by developing a series of possible outcomes and situations in which a given product, policy, or technology may find its application. Scenarios are based on a step-by-step development of a situation, meaning they can be either very precise or very wrong. Therefore, their use is limited to theory or individual cases, such as planning a city based on facts and evidence that do not have a great degree of variability. Thus, the fewer variables there are, the more precise a scenario can be (Gordon, 1992, p. 33).

2.2.4 Probability forecasts

Last but not least, there are probability forecasts, which differ significantly from the already described groups of methods. All mentioned approaches rely heavily on the past data; however, the probability is based on what the future might bring. It means that instead of focusing on past data, the method at hand uses factors that may appear in the future and which may influence the development of events or trends. A great example is given by Gordon (Gordon, 1992, p. 32), "let us suppose that we wanted to forecast future demand for electrical power (…). Any forecast of demand for power should consider future developments such as the possible emergence of electric automobiles, cogeneration, changes in the price of fuel, and changing public concern about nuclear energy. It appears that more than an extension of the past is required." This example is an excellent explanation of the probabilistic techniques. Simply, it shows that in order to make an accurate prediction, past data is relevant, but some futures factors have to be considered. The following table is a summary of forecasting methods and their application.

Table 2.2: Application of forecasting methods (Gordon, 1992, p. 34).

Technique	**Relative Complexity**	**Forecast Horizon**	**Data and Training**	**State of Development**	**Current Domain**
Genius forecasting	Low	Infinite	Low	Unexplored	All
Delphi questionnaires	Medium	Medium/long	Low	High	All
Delphi interviews	Medium	Medium/long	Low	High	All
On-line expert groups	Medium	Medium/long	Low	Improving	All
Time series analysis	Low	Short	Medium	High	Not political

Regression modeling	Medium	Short	Medium	High	Not political
Simulation Modeling	High	Short/medium	High	Improving	All
System dynamics	High	Short/medium	High	High	All
Trend-impact analysis	Low	Short/medium	Medium	High	Not political
Cross-impact analysis	Medium	Medium	Low	High	All
Interax	Medium	Medium	High	High	All

Scenarios	Medium	Short/long	Medium	High	All
Technology sequence analysis	High	Medium/long	High	Improving	Science, technology
Non-linear models	High	Medium	High	Frontier	Not political

2.3. Forecasting methods

2.3.1 Forecasting by averages

The first method to be described here is the average approach. Predictions are the same as the mean calculated from the past data. It can be used in many fields in which past data is available. The equation for the average method is presented below (Hyndman, 2018, p. 138).

$$\boldsymbol{\hat{Y}T + h|T = \bar{y} = (y_1 + \ldots + y_T)/T}$$

where

$\boldsymbol{\hat{Y}T + h|T}$ is a short-hand for the estimate of $\boldsymbol{YT + h}$

and $\boldsymbol{(y_1 + \ldots + y_T)}$ represents the past data

Besides its use in times series, it can also be used for cross-sectional data when forecast concerns values that are not included in the current data set.

In the average approach, the forecast value equals the mean value of all past data on demands. The first-year forecast is a guess, but it is already possible to start forecasting at the end of that period. Each forecast is made at the end of a given year because it is worth waiting and seeing the actual demand for each year before making a forecast.

Table 2.3 Making forecasts using the average approach.

Year	Actual Demand	Forecast	Comments
1	400	390	This was a guess due to a lack of relevant data
2	450	400	The forecast is based on all past data.
3	470	425	The forecast is the mean average of the past values of actual demand

2.3.1 Naïve forecasting

The second method to be described is naïve forecasts, which is among the most practical forecasting models for the cost-effectiveness ratio. The naïve approach is the best way to create comparisons of more complex forecasting models. However, the use of the naïve method is limited to time series data because the resulting forecasts are equal to the last observed value. It is especially effective for the fields of finances and economics, where patterns are difficult to predict accurately. The following equation is used for the naïve method in time series (Hyndman, 2018).

$$\boldsymbol{\widehat{Y}_{T+h|T} = YT}$$

The above table shows the forecast after the first year. In the example below, the naïve method is equal to this period's demand. Subsequent forecasts are based on the year-by-year calculation and estimation of probable demand.

Table 2.4: Creating forecasts using the naïve method.

Year	Demand	Forecast	Comments
1	400	------	There was no past data on demand, so the forecast was not possible
2	420	400	The forecast was based on the last known value of the demand.
3	470	420	Again, the forecast is the average value of the past values of actual demand. This situation is repeated every year.

2.3.3 Drift method

Another method, which is similar to the naïve one, is the drift method. It can be defined as a variation of the former because it allows for forecasts to either increase or decreases with time. The change over time is called the drift, and it is the average change observed based on the past data. $\boldsymbol{T+H}$ is calculated from the following equation (Hyndman, 2018, p. 140).

$$\boldsymbol{\widehat{Y}_{T+h|T} = YT + \frac{h}{T-1}\sum_{t=2}^{T}(y_t - y_{t-1}) = y_T + h(\frac{y_T - y_1}{T-1})}$$

Nevertheless, another variation of the naïve method is the seasonal naïve method, which concerns seasonality. The basic rule is that each prediction equals the last observed value of the same season. For instance, the value of prediction for all months after February will be the same as the previous value for February. If the value of February was 40, then all predictions will use 40 as the value of prediction. $T + H$ is calculated from the following equation (Hyndman, 2018, p. 140):

$$\boldsymbol{\widehat{Y}_{T+h|T} = Y_{T+h-m(k+1)}}$$

where

$\boldsymbol{m}$ is the seasonal period

$\boldsymbol{k}$ is the smallest integer greater than ***(h-1)/m***

The above examples are some of the time-series models, which base o past historical data in their estimation. However, there are also other methods of forecasts. For instance, there is a group of methods known as econometric forecasting methods. Their goal is to identify the underlying factors that might have an impact on the forecasted variable. Details such as rain patterns can be used when calculating the forecasted sale of umbrellas in the given season. Econometric methods are based on seasonality and consider regular seasonal variations.

Let us take football as an example; every four years, there is either a European Championship or World Cup taking place somewhere around the world. Forecasts connected with sales of national team t-shirts, gadgets and other items are developed by considering this fact. The same is with seasonality after the transfer window. Based on rumours and actual transfers of players, it is possible to predict the sale of sports outfits of the given club or even the number of tickets that the fans will buy just to see the new player in action. Apart from sport, the primary forecasting consideration in econometric methods is holidays and customs.

For instance, during Ramadan, the sale of water in Muslim countries will undoubtedly be higher due to feasting (Nahmias, 2009, pp. 45-50). Some methods in this type of forecasting use the forecaster's judgment instead of including mathematical algorithms. Another method is to consider past relations between variables.

Some of the most popular methods include regression analysis, a large group of methods used to predict future values based on other values, all of them being variables. Apart from parametric and non-parametric techniques based on linear and non-linear aspects of values, the group includes a method based on autoregressive moving average with exogenous inputs. The described methods are quantitative, and because of that, they are often judged against one another by comparing in-sample and out-of-sample mean square error. As already mentioned, one forecasting method can be a lot more accurate than the other; therefore, the already described GMDH is found to be more accurate than the traditional ARMA method (Li, et al., 2017).

A different approach to forecasting is the so-called judgmental forecasting, which incorporates intuitive judgment of the forecaster, opinions, and estimates based on subjective probability. Those methods are used when there are not enough past data to develop a forecast or new and unique conditions on the market. Some of the more popular judgmental methods are:

- composite forecasts,
- Cooke’s method,
- the Delphi method,
- forecasts by analogies (Hyndman, 2018, pp. 65-70).

2.4 Bayesian (state-space) methods for time series

It is well-known that the fundamental properties of financial processes are the occurrence of a unitary element and the time-varying variance of rates of return. The unit root is directly related to the random walk hypothesis, which states that shares or other financial instruments are equal to the price of shares in the previous period plus a random variable with an expected value equal to zero. It also assumes that price increases (rates of return) are independent of each other and have an identical probability distribution. The traditional understanding of random walk confirms the efficiency of the market, i.e. if prices are subject to random walk, it can be confirmed that the market is inefficient. All publicly available information about a given share is immediately reflected in the price. For this reason, many empirical studies focus on the ARIMA (Autoregressive Integrated Moving Average) models introduced by (Box & Jenkins, 1983), where asset prices are treated as fixed-incremental processes.

2.4.1 Random walk theory

This random walk of prices, commonly spoken about in the EMH school of thought, fails any investment strategy that aims to beat the market consistently. Managing futures portfolios is slightly different as transaction costs can be ignored due to their size relative to potential gains and losses. The EMH suggests that given the transaction costs involved in portfolio management, it would be more profitable for an investor to put his or her money into an index fund.

In the real world of investment, however, there are obvious arguments against the EMH. Some investors have beaten the market, such as Warren Buffett, whose investment strategy focused on undervalued stocks made billions and set an example for numerous followers. Some portfolio managers have better track records than others, and there are investment houses with more renowned research analyses than others. Some supporters of this view are not presenting their views in public as the knowledge they generate and use in trading is considered alpha; therefore, sharing it will deprive them of competitive advantage.

Another counterargument to the EMH state is the presence of consistent patterns. For example, the January effect is a pattern that shows higher returns tend to be earned in the first month of the year; and the weekend effect is the tendency for stock returns on Monday to be lower than those of the immediately preceding Friday.

Another well-known property of financial returns is volatility during conditional variance. The concentration of variance in narrow time intervals and the closely related variability of conditional variance is one of the essential financial characteristics of time series. In particular, significant price changes are preceded by equally large price changes, while their small changes often precede small price changes. The GARYCH (Generalized Autoregressive Conditional Heteroscedasticity) models proposed by (Engle, 1982 and Bollerslev, 1986) are designed to model the variable over time of conditional variance and describe other basic characteristics such as increased kurtosis or thick tails.

In (Swanson & Granger, 1997), it was shown that the processes that require the calculation of the first differences are not always precisely integrated processes of the first order. It is proved that macroeconomic and financial processes often have a unitary element, which is not permanent but random. The random parameter is treated as a stochastic process whose realizations oscillate around one. Most often, it is an autoregressive process or white noise. This implies that this type of process is stationary in the long term, but it can be non-stationary or even explosive in the short term. A model with time-varying parameters, created to describe a random unit element, is referred to as STUR (Stochastic Unit Root). It seems that due to the time-random parameter, this process can be classified into a wider group of models, namely double-stochastic models (Leybourne, et al., 1996).

From the point of view of sample properties, it seems interesting to compare the explanatory power of the STUR and GARCH models. Namely, whether and to what extent STUR models can describe the distinctive properties of financial processes better than GARCH models. The Bayesian inference is a good tool for achieving this goal. Its primary advantages include the possibility of presenting the entire distribution of each size of interest (as opposed to classical methods, where there is a point score and the associated standard error) and a relatively easy selection of the model by calculating a posteriori probability of both models and the corresponding odds ratio a posteriori (Leybourne, et al., 1996).

It is widely believed that asset prices are fixed incremental processes, where the degree of integration is one. The standard model for modeling both financial and macroeconomic series prices is the ARIMA model with constant (unchanging in time) structural parameters. Recent research in Bayesian inference (Jones & Marriott, 1999) and (Engle, 1982) and classical inference (Leybourne, et al., 1996).

2.4.2 STUR type process

Sollis (Sollis, 2004) indicated that financial and macroeconomic processes have an element whose values can fluctuate around time one. Models describing the dependencies mentioned above are referred to as STUR (Leybourne, et al., 1996 ; Swanson & Granger, 1997). The article applies to the STUR model, which they proposed by Sollis. The form of this model is more convenient when estimating parameters, and it is less troublesome in numerical calculations. Despite a slightly different representation, it seems, however, that both models have a similar interpretation.

STUR type processes for general price logarithms as:

$$\boldsymbol{Y_t = 100ln\,(P_t)}$$

can be saved in the form

$$\boldsymbol{y_t} = \quad a_t\ \boldsymbol{y_{t-1}} + \boldsymbol{\varepsilon_t}$$

where:

$$\boldsymbol{a_t = a_0 + \delta_t}$$

$$\boldsymbol{\delta_0 = 0}$$

$$\boldsymbol{\delta_t = \rho\delta_{t-1} + \eta_t}$$

It is assumed that the autocorrelation coefficient is in the range from ***-1*** to ***1***. Additionally, the assumption of mutual independence, Gaussian residual processes is assumed.

The processes $\varepsilon_t \sim N(0, \delta^2)$ and $\eta_t \sim N(0, \omega^2)$ are independent of each other.

For $a_0 = 1$ and $\omega^2 = 0$, y is a random walk process,

but if $a_0 = 1$ and $\omega^2 = 0$ this is a process whose average contains the unit root. This process is called a process with a stochastic unit element.

The analyzed model can also be saved in the form of:

$$\Delta y_t = \delta_t y_{t-1} + \varepsilon_t$$

$$\delta_t = \rho \delta_{t-1} + \eta_t$$

where

y_t means the observed process at time t, while ε_t and η_t they mean like previously Gaussian white noise with mean zero and variance independent of each other equal to δ^2 and ω^2. The equation therefore can be written in an equivalent form, namely:

$$y_t = (1 + \delta_t) y_{t-1} + \varepsilon_t$$

where

$\rho = 0$ and

$\omega^2 = 0$ is the parameter δ_t for all t, it takes values equal to zero and provides the random walk process.

2.4.3 GARCH process

Modeling time series of financial data is a major application and area of statistical research and probability theory in particular. One of the challenges related to this field is the presence of heteroskedastic effects, which means that the volatility of the considered process is generally not constant. Here the volatility is the square root of the conditional variance of the log return process given its previous values.
That is, if $\boldsymbol{P_t}$ is the time series evaluated at time t, one defines the log returns.

$$\boldsymbol{X_t = logP_{t+1} - logP_t}$$

and the volatility $\boldsymbol{\delta_t}$,
where

$$\boldsymbol{\delta_t^2 = \mathrm{VAR}[X_t^2 \mid \mathcal{F}_{t-1}]}$$

and $\boldsymbol{\mathcal{F}_{t-1}}$ is the $\boldsymbol{\delta}$ -algebra generated by $\boldsymbol{X_0, \ldots, X_{t-1}}$. Heuristically, it makes sense that the volatility of such processes should change over time, due to any number of economic and political factors, and this is one of the well known as "stylized facts" of mathematical finance.

Some financial models, such as the Black-Scholes model, ignore the presence of heteroskedasticity, which is widely used to calculate the fair pricing of European-style options. While this leads to a closed-form formula, it also makes assumptions about the stationarity of the underlying process, which may not be realistic in general. Another commonly used homoscedastic model is the Ornstein-Uhlenbeck process used in finance to model interest rates and credit markets. This application of a homoscedastic model is known as the Vasicek model, and it similarly suffers from the homoscedastic assumption.

ARCH (autoregressive conditional heteroskedasticity) models were introduced by Robert Engle (Engle, 1982) to account for this behavior. Here the conditional variance process is given an autoregressive structure, and the log returns are modelled as a white noise multiplied by the volatility:

$$\boldsymbol{X_t = e_t\, \delta_t}$$

where

$\boldsymbol{e_t}$ (the 'innovations') are i.i.d. with expectation 0 and variance 1 and are assumed independent from $\boldsymbol{\delta_k}$ for all $\boldsymbol{k \leq t}$. The lag length $\boldsymbol{P \geq 0}$ is part of the model specification and may be determined using the Box-Pierce or similar tests for autocorrelation significance, where the case $\boldsymbol{P = 0}$ corresponds to a white noise process. To ensure that $\boldsymbol{\delta_t^2}$ remains positive, $\boldsymbol{\omega, \alpha_i \geq 0} \ \forall_{\boldsymbol{i}}$ is required.

Tim Bollerslev (Bollerslev, 1986) extended the ARCH model to allow $\boldsymbol{\delta_t^2}$ to have an additional autoregressive structure within itself. The GARCH(1,1) (generalized ARCH) model is given by

$$\boldsymbol{X_t = e_t \, \delta_t}$$

$$\boldsymbol{\delta_t^2 = \omega + \alpha_1 X_{t-1}^2 + \ldots \alpha_p X_{t-p}^2 + \beta_1 X_{t-1}^2 + \ldots \beta_q X_{t-q}^2 .}$$

This model, particularly the simpler GARCH(1,1) model, has become widely used in financial time series modelling and is implemented in most statistics and econometric software packages.

GARCH(1,1) models are often preferred over other stochastic volatility models by many economists due to their relatively simple implementation: since stochastic difference equations give them discrete time, the likelihood function is easier to handle than continuous-time models financial data is generally gathered at discrete intervals. However, there are also improvements to be made on the standard GARCH model. A notable problem is the inability to react differently to positive and negative innovations, where in reality, volatility tends to increase more after a large negative shock than an equally large positive shock, also known as the leverage effect.

While the standard GARCH(1,1) and closely related GARCH(p,q) models are helpful tools in econometrics, they cannot describe certain aspects often found in time series derived from financial data. An important weakness is their inability to react differently to positive and negative innovations - the conditional variance considers only the squares of the innovations. However, many datasets display a leverage effect, where negative returns correspond to higher increases in volatility than positive returns. Another problem is the lack of clarity concerning stationarity and persistence, where shocks may persist in one norm but not in another in the GARCH model. The existence of almost-surely stationary GARCH(1,1) processes with in_nite variance at every time

$\boldsymbol{t}$ is inconvenient. An important variation of the GARCH model which addresses these problems is the Exponential ARCH (EARCH) model attributed to Nelson (Nelson, 1989). Its additional advantage is greater flexibility in the parameters by imposing the autoregressive relationship on $\boldsymbol{log\ \delta_t^2}$, which can take negative values. The general form of the EARCH(1) model is

$$\boldsymbol{log\ \delta_t^2 = \omega + \beta(|e_{t-1}| - \mathbb{E}[|\, e_{t-1}|]) + \gamma e_{t-1}}$$

It can also be shown that the conditions for stationarity, unlike the GARCH(1,1) model, are the same for both wide-sense (almost sure) and covariance stationarity. A necessary and sufficient condition for this is $\boldsymbol{\beta < 1}$. However, the asymptotic properties of QML estimation for EARCH models are not as well known as the GARCH case.

Another possible extension of the GARCH(1,1) model to allow for asymmetry is the QGARCH(1,1) model of Sentana (Sentana, 1995):

$$\boldsymbol{\delta_t^2 = \omega + \alpha X_{t-1}^2 + \beta_q \delta_{t-1}^2 + \gamma e_{t-1}}$$

where appropriate restrictions are necessary to ensure that $\boldsymbol{\delta_t}$ remains positive.

These are given by $\boldsymbol{\omega, \alpha, \beta > 0}$ and $\boldsymbol{|\gamma| \leq 2\sqrt{\alpha\omega}}$ Many of the properties of the GARCH(1,1) model carry over immediately to QGARCH. For example, the QGARCH model has unconditional variance $\boldsymbol{\frac{\omega}{1-\alpha-\beta}}$ if $\boldsymbol{\alpha + \beta < 1}$ and undefined otherwise, and $\boldsymbol{\alpha + \beta < 1}$ is also necessary for covariance stationarity.

The AGARCH(1,1) (asymmetric GARCH) model developed by Engle and Ng (Engle & Ng, 1993) is another approach to allowing the GARCH model to react asymmetrically. It is defined by

$$\boldsymbol{X_t = e_t\, \delta_t}$$

$$\delta_t^2 = \omega + \alpha(X_{t-1} + \gamma)^2 + \beta\delta_{t-1}^2$$

where

γ is the non-centrality parameter.

Another interesting model is the TGARCH(1,1) (threshold GARCH) model developed by Jean-Michel Zakoian (Francq & Zakoian, 2009). Here, the autoregressive specification is given for the conditional standard deviation instead of the variance:

$$X_t = e_t \delta_t$$

$$\delta_t = \omega + \alpha^+ X_{t-1}^+ + \alpha^- X_{t-1}^- + \beta\delta_{t-1}$$

where $X_t^+ = max\{0, X_t\}$ is the positive part of X_t and $X_t^+ = min\{0, X_t\}$ the negative. This is another model developed to account for asymmetric reactions to shocks, which has the advantage of being closer to the original GARCH formulation but also requires some non-negativity assumptions for the parameters.

2.4.4 Cox Process for modeling events

A Cox process, also recognized as a doubly stochastic Poisson method in probability theory, is a point process that is a Poisson process generalization where the time-dependent intensity is itself a stochastic process. The method is named after David Cox, a statistician who first released the model in 1955. Cox processes are used to generate simulations of spike trains (the sequence of neuron-generated action potentials) and financial mathematics. They create a valuable framework for modeling prices of financial instruments in which credit risk is a significant factor (Cox, 1955).

In this document, of particular interest is the Cox process, where the two most prevalent ones are: the Markov modulated Poisson process (MMPP) and the Gaussian process modulated

Cox process (GPCox). Widespread in statistics, the MMPP considers $\lambda(t)$ as a random sample (trajectory) from a continuous-time Markov chain. The GPCox is a nonparametric Bayesian model made by placing a Gaussian process (GP) prior on $\lambda(t)$. The model has a finite set of intensity levels, and the latent state regulates which intensity level is used at any given moment. The GPCox has established important consideration in the machine learning community for the last decade for its flexible nonparametric modeling with principled uncertainty treatment.

The MMPP is adequate at modeling highly diverse intensity phases: bursty events for some intervals and rare events for others (Doerr et al., 2013). Conversely, there can be sudden intensity changes amongst these regimes, which may be unnatural in certain circumstances. Moreover, for the interval under a given latent state, the model follows a constant intensity (i.e., a homogeneous process), which may limit its representational capacity. The GPCox, on the other side, promotes smooth improvements in intensity over time. The disadvantage, however, is that the dramatic changes in intensity are not handled correctly unless an extremely non-smooth kernel is adopted, which can generally occur when there is a large quantity of information.

So, the primary concept in this chapter is to present a new model that will take advantage of both models. Like the MMPP, we consider an underlying Markov Chain of Continuous Time (CTMC), which produces a latent state path (say, r various states). With their own GP priors, we incorporate r latent functions, each of which serves as the intensity responsible for each of the r states (Doerr et al., 2013). Thus, this model can model significant intensity regime changes (possibly abrupt) via the CTMC dynamics, and at the same time, it also enjoys the smooth intensity modeling of the GP, which is not constant within the interval under a given latent state. Our model, known as the Gaussian Cox Process (MMGCP) modulated by Markov, has more representation than the prior two models.

Both models are subsumed as special cases: if the GP priors put all their masses into constant functions, we end up with the MMPP, and ii) if $r = 1$ (single-state), then the model reduces to the GPCox (Gelman, et al., 2003).

The two earlier models show extreme features in terms of time-stationarity. Since the CTMC is stationary and the intensity under a given state is a constant invariant of t, the MMPP makes $\pi(t)$ fully stationary (i.e. time-independent). On the other hand, the GPCox builds a fully non-stationary (time-variant) $\lambda(t)$ on top of the kernel function defined over t. In some ways, the MMGCP aims to model a so-called semi-stationary intensity function in that stationary CTMC dynamics govern the change in the macro-scale intensity regime (Gelman, et al., 2003), while the intensity is modeled as a smooth time-variant function within each regime. In this context, an optimal situation for our model is as follows: there are r fundamental candidate intensity functions $\{\lambda^i(t)\}_{i=1}^r$ where at a specified moment t, which of these applicants is active, is determined by the stationary r-state Markov system $X(t)$, i.e. $\lambda^{X(t)}(t)$. The model also imposes these candidate features on the GP before accounting for uncertainty and allowing more flexibility in modeling. Not only do we introduce this situation as a synthetic setup in the evaluations, but we also show on some actual datasets that our MMGCP outperforms the prior models considerably (Gelman, et al., 2003).

Next section focuses on modeling occurrences that may happen over the horizon of set moment $[0, T]$. Poisson process produces the inhomogeneous events , which can be fully defined by the non-negative intensity function $\lambda : [0, T] \rightarrow \mathbb{R}_+$. It defines the rate of occurrence of the event (i.e. the probability of occurrence during the interval of infinitesimal $[t, t + dt]$ is $\lambda(t)dt$). Then the log-likelihood of observing the event data is

$$\mathcal{D} = \{t_1, \ldots, t_N\} \; (\subset [0, T])$$

which can be denoted as follows:

$$\log P(\mathcal{D} \mid \lambda(\cdot)) = \sum_1^N \log \lambda(t_n) - \int_0^T \lambda(t)\, dt. \qquad (1)$$

It is prevalent in statistics to suppose a particular parametric shape for $\lambda(t)$, then estimate it with (1) by the criterion of highest probability (Lee, et al., 1991). The Cox process, on the contrary, further considers $\lambda(t)$ as a random process. Below are briefly outlined two of the most common ones.

Markov Modulated Poisson Process (MMPP)

This model is essentially continuous $\lambda(t)$. Particularly r constant intensity levels can be observed $\{\bar{\lambda}_1, \ldots, \bar{\lambda}_R\}$, but which level is determined at a given moment by the latent Markov process $X : [0, T] \rightarrow \{1, \ldots, r\}$ which is ran by a continuous-time Markov chain (CTMC). An r-state CTMC is specified by the initial state probability

$$\pi_i = P(X(0) = i) \text{ for } i = 1,\ldots,r$$

and the transition rate matrix Q whose off-diagonal Q_{ij} $(i \neq j)$ defines the probability rate of state change from i to j, namely

$$Q_{ij} = \lim_{\Delta t \rightarrow 0} \frac{P(X(t+\Delta t) = j | X(t) = i)}{\Delta t}. \quad (2)$$

Describing diagonal entries as $Q_{ij} := -\sum_{j \neq i} Q_{ij}$ allows the probability of staying at state i for duration h to be $e^{hQ_{ii}}$. This model does not have a time-variant component, which is sufficient to model stationary event data. There are renowned algorithms for EM learning for approximating the factors of the model (Simma & Jordan, 2010).

Gaussian Cox Process (GPCox)

The GPCox model has a latent f(t) function distributed a priori through a Gaussian method that determines the intensity function as $\lambda(t) = \rho(f(t))$ where $\rho(\cdot)$ is a non-negative link function, for instance, sigmoid, exponential or square function. The posterior inference $P(f(\cdot)/\mathcal{D})$ is interesting mainly due to the integration in the likelihood function (1). Besides the overhead computational assessment of the integral, latent function values must be calculated for all outputs $t \in [0, T]$, not only those t in information D as in most standard GP models (Simma & Jordan, 2010). Consequently, some former approaches had to resort to discretizing the time domain ((Vanhatalo, 2013)). Recently, several sophisticated inference methods have been proposed to address this difficulty. Simma (Simma & Jordan, 2010) formed tractable MCMC dynamics by exploiting the idea of thinning-based sampling in the Poisson process. However, its time complexity is cubic in the data size, which is often prohibitive for large-scale problems.

Vanhatalo (Vanhatalo, 2013) proposed an alternative thinning strategy by sampling from a non-uniform intensity process to deal with the scalability, while (Simma & Jordan, 2010) introduced inducing points within the MCMC sampler. Vanhatalo (Vanhatalo, 2013) used a positively transformed intensity function for direct numerical integration and interpolation. In parallel, (Lloyd, et al., 2016) derived analytic formulation for the scalable variational inference using the square link function and the pseudo input treatment (Titsias, 2009) (Galliani, et al., 2016).

Markov Modulated Gaussian Cox Process

In this passage, a model that can take benefits from previous models in previous passages is described. Consider that latent functions underlying r are dedicated to representing distinct features of the intensity function.

Written in such a way:

$$\boldsymbol{f}(\cdot) := \{\boldsymbol{f}^{\,\boldsymbol{i}}(\cdot)\}_{\boldsymbol{i=1}}^{\boldsymbol{r}},$$

they are expected to be autonomously GP distributed a priori.

That is,

$$\boldsymbol{P}(\boldsymbol{f}(\cdot)) = \boldsymbol{P}(\boldsymbol{f^i}(\cdot),\ldots,\boldsymbol{f^r}(\cdot)) = \prod_{\boldsymbol{i=1}}^{\boldsymbol{r}} \boldsymbol{P}(\boldsymbol{f^i}(\cdot)) \qquad (3)$$

where

$$\boldsymbol{f^i}(\cdot) \sim \boldsymbol{\mathcal{GP}}\,(\boldsymbol{m^i}(\cdot), \boldsymbol{k^i}(\cdot,\cdot))\,, \boldsymbol{i} = \boldsymbol{1},\ldots,\boldsymbol{r}$$

Latent Markov process ***X(t)*** is introduced to determine which of these $\boldsymbol{r}$ functions is responsible for the intensity at each time, similar to the MMPP generated from a $\boldsymbol{r}$-state CTMC$\boldsymbol{(Q,\pi)}$. The intensity at the moment t is then determined by $\boldsymbol{f}^{\,X(t)}$; likewise, we use the square link function as (Lloyd et al., 2015), which is resulted in:

$$\boldsymbol{\lambda(t)} \mid \boldsymbol{f}(\cdot), \boldsymbol{X}(\cdot) = (\boldsymbol{f}^{\,X(t)})^{\boldsymbol{2}} \quad (4)$$

The complete joint distribution of the model therefore can be re-written as:

$$\boldsymbol{P}(\boldsymbol{\mathcal{D}}, \boldsymbol{X}(\cdot), \boldsymbol{f}(\cdot)|\boldsymbol{\Theta}, \Omega) = \boldsymbol{P}(\boldsymbol{f}(\cdot)|\boldsymbol{\Theta}) \times \boldsymbol{P}(\boldsymbol{\mathcal{D}}|\boldsymbol{X}(\cdot), \boldsymbol{f}(\cdot)) \quad (5)$$

where $\boldsymbol{\Theta} = \{\boldsymbol{\theta_m}, \boldsymbol{\theta_k}\}$ is the parameters of the mean and covariance functions of the prior GP (e.g., $\boldsymbol{\theta_k} = \{\boldsymbol{\theta_k^i}\}_{i=1}^{r}$ with $\boldsymbol{\theta_k^i}$ denoting the parameters of the covariance function $\boldsymbol{k^i}(\cdot,\cdot)$ $\boldsymbol{for}\ \boldsymbol{f^i}(\cdot)$). The CTMC parameters are denoted by $\boldsymbol{\Omega = \{Q, \pi\}}$. Therefore Θ and Ω constitute the model parameters of the MMGCP. Due to the state trajectory and latent features, the last two terms in the RHS of (5) correspond to the probability of the state trajectory under the CTMC and the probability of information.

In order to officially derive these probabilities, it is useful to divide the horizon ***[0, T]*** by a realized trajectory of the state $\boldsymbol{X(\cdot)}$. Assume that a realization $\boldsymbol{X(\cdot)}$ undergoes $\boldsymbol{(L-1)}$ state changes during $\boldsymbol{[0, T]}$. Denoted by ul the time epoch when the $\boldsymbol{l}$-th state change occurs $\boldsymbol{(l = 1, \ldots, L-1)}$ with $\boldsymbol{u_0} = 0$ and $\boldsymbol{u_0} = \mathrm{T}$ for convenience. Let $\boldsymbol{s_l} \in \{\boldsymbol{1}, \ldots, \boldsymbol{r}\}$ be the state during the interval $(\boldsymbol{u_{l-1}}, \boldsymbol{u_l})$, and $\Delta\boldsymbol{u_l}$ be the length of the interval (i.e., $\Delta\boldsymbol{u_l} = \boldsymbol{u_l} - \boldsymbol{u_{l-1}}$. Note that these variables $\{\boldsymbol{u_l}, \boldsymbol{s_l}, \Delta\boldsymbol{u_l}\}_{\ l}$ are determined by the realization $\boldsymbol{X(\cdot)}$, and conversely, in a one-to-one way.

Looking into the likelihood of $\boldsymbol{X}$ restricted to each interval $(\boldsymbol{u_{l-1}}, \boldsymbol{u_l})$, it is composed of two steps:

i) no state change during $(\boldsymbol{u_{l-1}}, \boldsymbol{u_l})$, and

ii) state change from $\boldsymbol{s_l}$ to $\boldsymbol{s_{l+1}}$ right at the moment $\boldsymbol{u_l}$.

For the last interval $\boldsymbol{(l = L)}$, it only involves the step i). From the well-known $CTMC^2$ theorems, the first phase likelihood is $\boldsymbol{exp}(\Delta\boldsymbol{u_l}\ \boldsymbol{Q_{slsl}})$, while the second phase being $\boldsymbol{Q_{slsl+1}}$. Combining these over $\boldsymbol{l = 1, \ldots, L}$ and including the initial state probability $\boldsymbol{P}(\boldsymbol{X}(\boldsymbol{0}) = \boldsymbol{s_l}) = \boldsymbol{\pi_{s1}}$, the likelihood of the state trajectory is as follows

$$\boldsymbol{P}(\boldsymbol{X}(\cdot)|\Omega) \;=\; \boldsymbol{\pi_{s1}} \;\times\; \prod_{l=1}^{L} \boldsymbol{e}^{\Delta ulQ_{slsl}} \times \prod_{l=1}^{L-1} \boldsymbol{Q_{slsl+1}} \,. \quad (6)$$

To derive the likelihood of observing $\boldsymbol{\mathcal{D}}$ given $\boldsymbol{X(\cdot)}$ and $\boldsymbol{f(\cdot)}$, we let $\{\boldsymbol{t_1^l}, \ldots, \boldsymbol{t_{k1}^l}\}$ be the event times in $\boldsymbol{\mathcal{D}}$ that fall into the interval $\boldsymbol{\mathcal{I}_l} := [\boldsymbol{u_{l-1}}, \boldsymbol{u_l}]$. Within $\boldsymbol{\mathcal{I}_l}$, the intensity is fixed as $\boldsymbol{\lambda^{sl}(t)} := (\boldsymbol{f^{sl}(t)})^{\,\boldsymbol{2}}$, and applying the Poisson process likelihood gives:

$\boldsymbol{\lambda^{sl}(t_1^l)\ldots\lambda^{sl}(t_{kl}^l)exp(-\int_{\mathcal{I}_l}\lambda^{sl}\,(t)dt}$ and multiplying them over $\boldsymbol{l=1,\ldots,L}$ produces:

$$\boldsymbol{P}(\boldsymbol{\mathcal{D}}, \boldsymbol{X}(\cdot), \boldsymbol{f}) \;=\; \prod_{\substack{1\le l\le L,\\ n:t_n\in\mathcal{I}_l}} (\boldsymbol{f^{sl}}(\boldsymbol{t_n}))^2 \times \boldsymbol{e}^{-\int_{\mathcal{I}_l} \boldsymbol{\lambda^{sl}(t)dt}} \,. \;(7)$$

This section analyzed the log-Gaussian Cox procedures which may be applied to predict prices of the futures contracts. This type of model is especially suitable for representing semi-stationary data series such as prices of futures or other financial instruments. The model utilizes a hidden Markov process to capture and predict regime switches. This hidden process makes the model Grey-box because it allows selecting variables based on their importance, but the exact way they influence the predictions cannot be quantified. The methods suggested were initially used for data series from natural sciences, albeit they are generalizable to other issues and may bring several advantages in the fields of finance and economics.

2.4.5 Application of state-space view

It has long been suggested that the application of state-space modeling can be used to predict regime changes in time series data (Spencer, et al., 2010).

Ives and Dakos (Ives & Dakos, 2012) explored the detection of regime shifts by splitting time series data into time-varying and threshold models. They expanded on the suggestion of Scheffer (Scheffer, 2001) that time series dynamics may experience abrupt transitions between alternative stable states, often termed regime shifts. Although their work concentrated on ecological dynamics, the concept can be translated into time series data that captures prices of base or derivative financial instruments.

Although regime shifts are difficult to predict, recent work has proposed a series of statistical properties that change in predictable ways before a system shifts to an alternate state, and these properties can be used as generic early warning signals (Scheffer & al., 2009), (Clarke & Signorino, 2010). In theory, the majority of these signals are manifestations of critical change in a slope of a trend line, as a bifurcation is approached at which the system shifts to the alternative state (Strogatz, 1994). Different studies suggested that generic early warning signals include an increase in the variance (Carpenter & Brock, 2011), a decline in recovery rate (Scheffer 2007), an increase in autocorrelation (Held & Kleinen, 2004) and a peak of skewness (Guttal & Jayaprakash, 2008). Interestingly, almost all of the research mentioned above was performed using time series data from ecological systems.

Locally linear state-space models can be employed to anticipate regime shifts and to identify alternative stable states and have potential advantages over often used metric-based approaches. The existence and magnitude of these advantages will vary according to which methods are compared and what types of data are analyzed.

Ives and Dakos (Ives & Dakos, 2012) built on a standard Autoregressive Model.

$$\boldsymbol{x(t) = b_0 + \sum_{i=1}^{p} b_i(x(t-i) - b_0) + \varepsilon(t)} \qquad (1)$$

To introduce the Time-Varying model:

$$\boldsymbol{x(t) = b_0(t-1) + \sum_{i=1}^{p} b_i(t-1) \times (x(t-i) - b_0(t-1)) + \varepsilon(t)} \quad (2)$$

$$\boldsymbol{b_i(t) = b_i(t-1) + \phi_i(t)}$$

The top equation is a standard AR(p) model, however the coefficients are expressed as functions of time, and the bottom equation allows the autoregression coefficients $\boldsymbol{b_i(t)(i \geq 0)}$ to vary as random walks, with the rates of the random walks dictated by the variances $\boldsymbol{\delta_i^2}$ of

$\phi_i(t)$. Although in principle, the values of the autoregressive coefficients are unbounded (since they follow random walks), the values are constrained by fitting to the data. In addition to the process Eq. 2, we assume that there is a measurement equation

$$x^*(t) = x(t) + \alpha(t) \quad (3)$$

where:

$x^*(t)$ is the observed value of the state variable

$\alpha(t)$ is a Gaussian random variable with mean zero and variance δ_α^2 a depicting measurement error.

The following is the self-exciting threshold autoregressive state-space model, SETARSS(p), which assumes that there are two possible AR(p) models governing dynamics, with the possibility that the state variable switches between them when it crosses a threshold.

$$x(t) = b_0 + \sum_{i=1}^{p} b_i(x(t-i) - b_0) + \varepsilon(t) \text{ when } x(t-1) > c$$

$$x(t) = b_0 + \sum_{i=1}^{p} b_i' (x(t-i) - b_0') + \varepsilon(t) \text{ when } x(t-1) \leq c \quad (6)$$

where the coefficients b_i and b_0' (i . $0, \ldots, p$) denote separate sets of coefficients; this is the SETAR model (Tong, 1990) that assumes no measurement error. Here, we assume that there is a measurement error that does not differ between the two AR(p) systems and is therefore given by Eq. 3. As with the time-varying models, the SETARSS(p) is conditionally Gaussian, and therefore the Kalman filter can be used to compute its exact likelihood. In addition to the two sets of autoregression parameters b_i and b_i' , parameters to be estimated are the threshold c , the variance of the process error δ_ε^2 , and the variance of the measurement error δ_α^2 .

A first potential advantage is that the approaches we have presented are model-based, with the analyses producing a structurally simple linear autoregressive model with statistically fitted parameters. Autoregressive models can avoid challenges and subjective decisions that are inherent in metric-based approaches, such as deciding whether and how to filter or detrend data, and choosing the best rolling window for calculating the metric (Dakos & al., 2008), as both filtering and rolling window size may have a strong influence on whether a metric predicts a regime shift (Lenton, 2011).

Second, our model-based approach uses maximum likelihood estimation, thereby admitting a full range of statistical inference, including hypothesis testing, confidence intervals on coefficients, and model selection.

Third, as a state-space model, measurement error can be included as either user-defined input or, as we have illustrated here, a parameter estimated in the model. Measurement error introduces short-term (non-autocorrelated) variation to time-series data, yet critical slowing down by definition involves autocorrelated variation.

Fourth, our approach should have good statistical power because it incorporates the full information about the time series. This being said, the power of any statistical method will depend on the length and the underlying signal of a time series.

A significant contribution to the application of the state-space approach to time series was made by then Google engineer Steven L. Scott (Larsen, 2016), who created the BSTS (Bayesian structured time series) package using open source R software (Scott, 2017). The package includes many options to fit state-space models, including local and semi-local linear trends and dynamic regression components for state specification. These components of the state part of the model may be of particular interest for futures traders as a timely prediction of changes in local trends can be used to determine position entry timing.

The local linear trend model assumes that both the mean and the slope of the trend follow random walks. The equation for the mean is

$$\boldsymbol{\mu_{t+1} = \mu_t + \delta_t + \epsilon_t}$$

where $\boldsymbol{\epsilon_t \sim \mathcal{N}(0, \delta_\mu)}$

The equation for the slope is

$$\boldsymbol{\delta_{t+1} = \delta_t + \eta_t}$$

where $\boldsymbol{\eta_t \sim \mathcal{N}(0, \delta_\delta)}$

The prior distribution is on the level standard deviation $\boldsymbol{\delta_\mu}$ and the slope standard deviation $\boldsymbol{\delta_\delta}$.

The semi-local linear trend model is similar to the local linear trend but more useful for long-term forecasting. It assumes the level component moves according to a random walk, but the slope component moves according to an AR1 process centered on a potentially nonzero value $\boldsymbol{D}$. The equation for the level is

$$\boldsymbol{\mu_{t+1} = \mu_t + \delta_t + \epsilon_t}$$

where $\boldsymbol{\epsilon_t \sim \mathcal{N}}(1, \boldsymbol{\delta_\mu})$

The equation for the slope is

$$\boldsymbol{\delta_{t+1} = D + \phi(\delta_t - D) + \eta_t}$$

where $\boldsymbol{\eta_t \sim \mathcal{N}}(1, \boldsymbol{\delta_\delta})$

This model differs from the local linear trend model in that the latter assumes the slope $\boldsymbol{\delta_t}$ follows a random walk. A stationary AR(1) process is less variable than a random walk when making projections far into the future, so this model often gives more reasonable uncertainty estimates when making long term forecasts.

The prior distribution for the semi-local linear trend has four independent components. These are:

- an inverse gamma prior on the level standard deviation $\boldsymbol{\delta_{\mu}}$,
- an inverse gamma prior on the slope standard deviation $\boldsymbol{\delta_{\delta}}$,
- a Gaussian prior on the long run slope parameter $\boldsymbol{D}$,
- and a potentially truncated Gaussian prior on the AR1 coefficient $\boldsymbol{\phi}$. If the prior on $\boldsymbol{\phi}$ is truncated to (-1, 1), then the slope will exhibit short term stationary variation around the long run slope $\boldsymbol{D}$.

Dynamic regression component is a regression model where coefficients change over time according to a random walk. For the standard "random walk" coefficient model, the model is

$$\boldsymbol{\beta_{i,t+1} = beta_{i,t} + \epsilon_t}$$

where $\boldsymbol{\epsilon_t \sim \mathcal{N}(0, \delta_i^{\,2}/variance_{xi})}$

$\boldsymbol{\frac{1}{\delta_i^2} \sim Ga(a, b)}$ and $\boldsymbol{\sqrt{b/a} \sim sigma.mean.prior}$

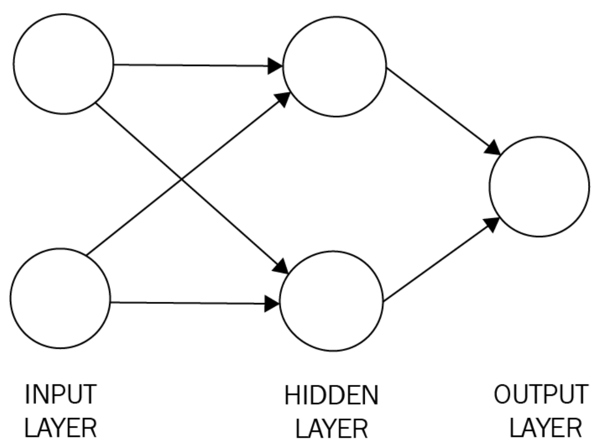
$\boldsymbol{a \sim shrinkage.parameter.prior}$

Each coefficient evolves independently, with its own variance term which is scaled by the variance of the ***i***'th column of ***X***. The parameters of the hyperprior are interpretable as: $\boldsymbol{\sqrt{\frac{b}{a}}}$ typical amount that a coefficient might change in a single time period, and 'a' is the 'sample size' or 'shrinkage parameter' measuring the degree of similarity in ***sigma[i]*** among the arms. We hope $\boldsymbol{\frac{b}{a}}$ is small in most cases, so that ***sigma[i]***'s will be small and the series will be forecastable. We also hope that 'a' is large because it means that the ***sigma[i]***s will be similar. The default prior distribution is a pair of independent Gamma priors for $\boldsymbol{\sqrt{\frac{b}{a}}}$ and ***a***. The mean of ***sigma[i]*** is set to ***.01 * sd(y)*** with shape parameter equal to 1. The mean of the shrinkage parameter is set to 10, but with shape parameter equal to 1. If the coefficients have AR dynamics, then the model is that each coefficient independently follows an AR(p) process, where the ***lags*** argument gives p. Independent priors are assumed for each coefficient's model, with a uniform prior on AR coefficients (with support restricted to the finite region where the process is stationary), while the ***sigma.prior*** argument gives the prior for each coefficient’s innovation variance.

2.4.6 Deep Learning methods for time series forecasting

Neural Networks (NN) are computing systems based on a collection of connected units or nodes called artificial neurons. Figure XX.X. A multilayer perceptron (MLP) is a class of feedforward NN consisting of at least three layers: input, output and at least one hidden layer. MLP utilizes a supervised learning technique called backpropagation for training (Goodfellow, 2016). Its multiple layers and non-linear activation functions allow to distinguish data that is not linearly separable (Cybenko, 1989).

Figure 2.8: Generic Neural Network Diagram



Deep learning neural networks can support multiple inputs and outputs and automatically learn arbitrary complex mappings from inputs to outputs (Brownlee, 2019). Such powerful features offer much promise for time series forecasting, especially when applied to problems with complex-nonlinear dependencies, multivalent inputs, and multi-step forecasting. Some methods have built-in feature engineering functions that allow for some understanding of how input variables influence outputs and may be considered grey-box models.

They are generally considered black-box models; they do not offer much to interpret the importance of the input variables.

Time series forecasting methods like ARIMA traditionally dominated the field because they are well understood and effective when applied to many types of problems. Nevertheless, these classical methods also have numerous limitations, such as:

- Focus on complete data: missing or corrupt data is generally unsupported.
- Focus on linear relationships: assumption of a linear relationship excludes more complex joint distributions.
- Focus on fixed temporal dependence: the relationship between observations at different times and the number of lag observations provided as input have to be identified and specified.
- Focus on univariate data: many real-world problems have multiple input variables.
- Focus on one-step forecasts: many real-world problems require forecasts with a long time horizon.

Simpler neural networks such as the Multilayer Perceptron or MLP work by approximating a mapping function from input variables to output variables. This general capability is valuable for time series for several reasons.

- Robust to Noise. Neural networks are robust to noise in input data and in the mapping function and can even support learning and prediction in the presence of missing values.
- Non-linear. Neural networks do not make strong assumptions about the mapping function and readily learn linear and non-linear relationships.

The capabilities of deep learning neural networks suggest a good fit for time series forecasting.

By definition and with enough resources, neural networks, in general, should be able to subsume the capabilities of classical linear forecasting methods given their ability to learn the arbitrary complex mapping from inputs to outputs. Therefore, neural networks can learn arbitrary mapping functions.

It is good practice to manually identify and remove systematic structures from time series data to make the problem easier to model (e.g. make the series stationary), and this may still be a best practice when using recurrent neural networks. This practice, however, may not help to identify regime changes. However, the general capability of these networks suggests that this may not be a requirement for a useful model. Theoretically, the available context of the sequence provided as input may directly allow neural network models to learn both trend and seasonality. Neural networks may not require a scaled or stationary time series as input.

Convolutional Neural Networks or CNNs are a type of neural network designed to handle image data efficiently. They have proven effective in challenging computer vision problems, achieving state-of-the-art results on tasks like image classification and providing a component in hybrid models for entirely new problems such as object localization, image captioning, and more. They achieve this by operating directly on raw data, such as raw pixel values, instead of domain-specific or handcrafted features derived from the raw data. The model then learns how to automatically extract the features from the raw data directly useful for the problem being addressed. This is called representation learning, and the CNN achieves this in such a way that the features are extracted regardless of how they occur in the data, so-called transform or distortion invariance.

Recurrent neural networks, also called RNNs, are those types of neural networks that use an output of

the network from a previous step as an input in an attempt to automatically learn across sequence data. The Long-Short-Term Memory, or LSTM, network is a type of RNN whose implementation addresses the general difficulties in training RNNs on sequence data that results in a stable model. It achieves this by learning the weights for internal gates that control the recurrent connections within each node. Although developed for sequence data, LSTMs have not proven effective on time series forecasting problems where the output is a function of recent observations, e.g. an autoregressive type forecasting problem, such as the car sales dataset. Nevertheless, LSTM models can be developed for autoregressive problems and use to compare with other neural network models.

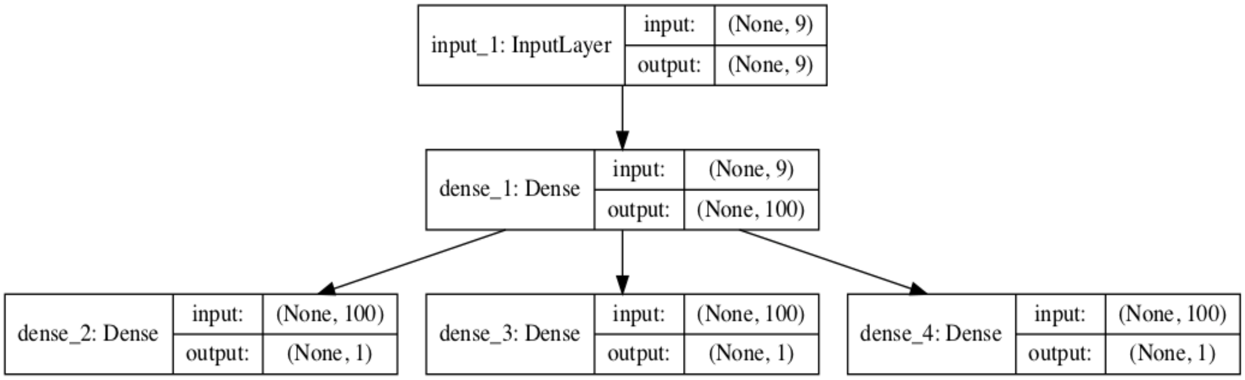
Each of the three discussed classes of neural network models, MLPs, CNNs and RNNs, offer capabilities and potential solutions that are challenging for classical time series forecasting methods, namely:

- Neural networks support multivariate inputs.
- Neural networks support multi-step outputs.

Even though MLPs can operate directly on raw observations, CNNs offer efficiency and much better performance at automatically learning to identify, extract and distil useful features from raw data. Convolutional neural networks support efficient feature learning. Although MLPs and CNNs can learn arbitrary mapping functions, the explicit addition of support for input sequences in RNNs offers efficiency and improved performance for automatically learning the temporal dependencies both within the input sequence and from the input sequence to the output. LSTM networks support efficient learning of temporal dependencies.

These capabilities can also be combined, such as using hybrid models like CNN-LSTMs and ConvLSTMs that seek to harness the capabilities of all three model types. Hybrid network models have the ability to combine the diverse capabilities of different network architectures efficiently. Similarly to multiple input series, there is another, more elaborate way to approach modeling of the problem. A separate output MLP model can be applied to each output series. It is often defined as a multi-output MLP approachl. It may offer more flexibility or better performance depending on the specifics of the problem that is being modeled. The schematic below clearly shows a model with three separate output layers of the model and each layer's input and output shapes to showcase a model architecture (Dorffner, 1996).

Figure 2.9: Multi-output MLP for Multivariate Time Series Forecasting (Ming & al., 2014).

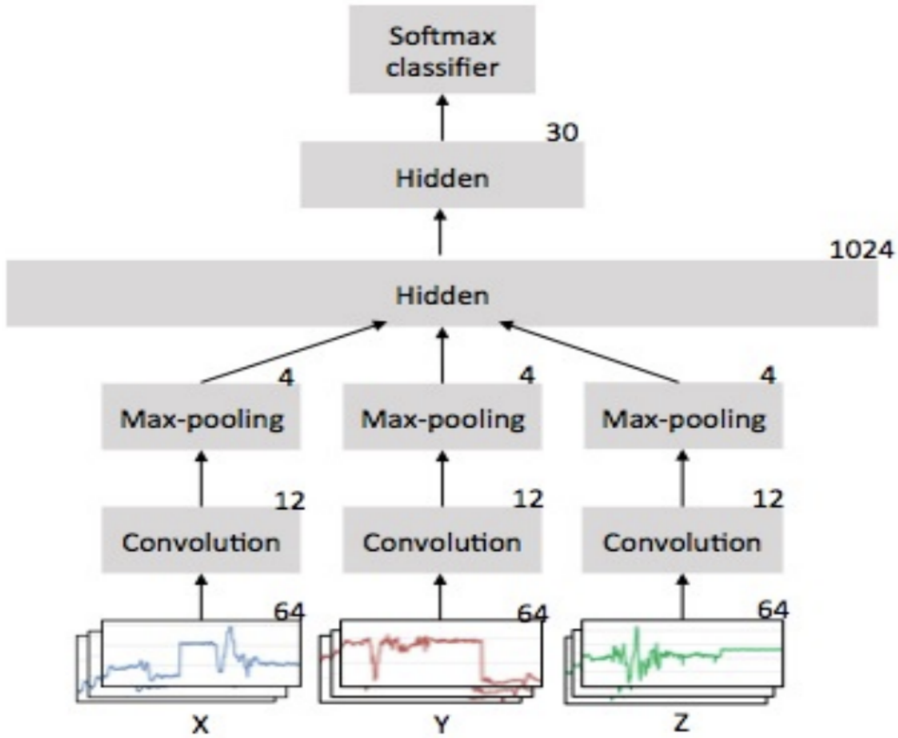


An important contribution of neural networks is their elegant ability to approximate arbitrary non-linear functions. A subfield of forecasting may be able to extract high value by utilizing this property in time series processing and promises more powerful applications (Dorffner, 1996).

Deep neural networks called Convolutional Neural Network models, or CNNs for short, were developed to use image data such as handwriting recognition. More recently, CNNs have been used for time series forecasting. The CNN model learns to map a given window of signal data to an activity where the model reads across each window of data and prepares an internal representation of the window.

The first important work using CNNs for Human Activity Recognition or HAR was by Ming (Ming & al., 2014) in their 2014 paper Convolutional Neural Networks for Human Activity Recognition using Mobile Sensors. In the paper, the authors develop a simple CNN model for accelerometer data, where each axis of the accelerometer data is fed into separate convolutional layers, pooling layers, then interpreted by hidden fully connected layers after concatenation. The figure is below taken from the paper clearly shows the topology of the model. It provides a good template for how the CNN may be used for HAR problems and time series classification in general.

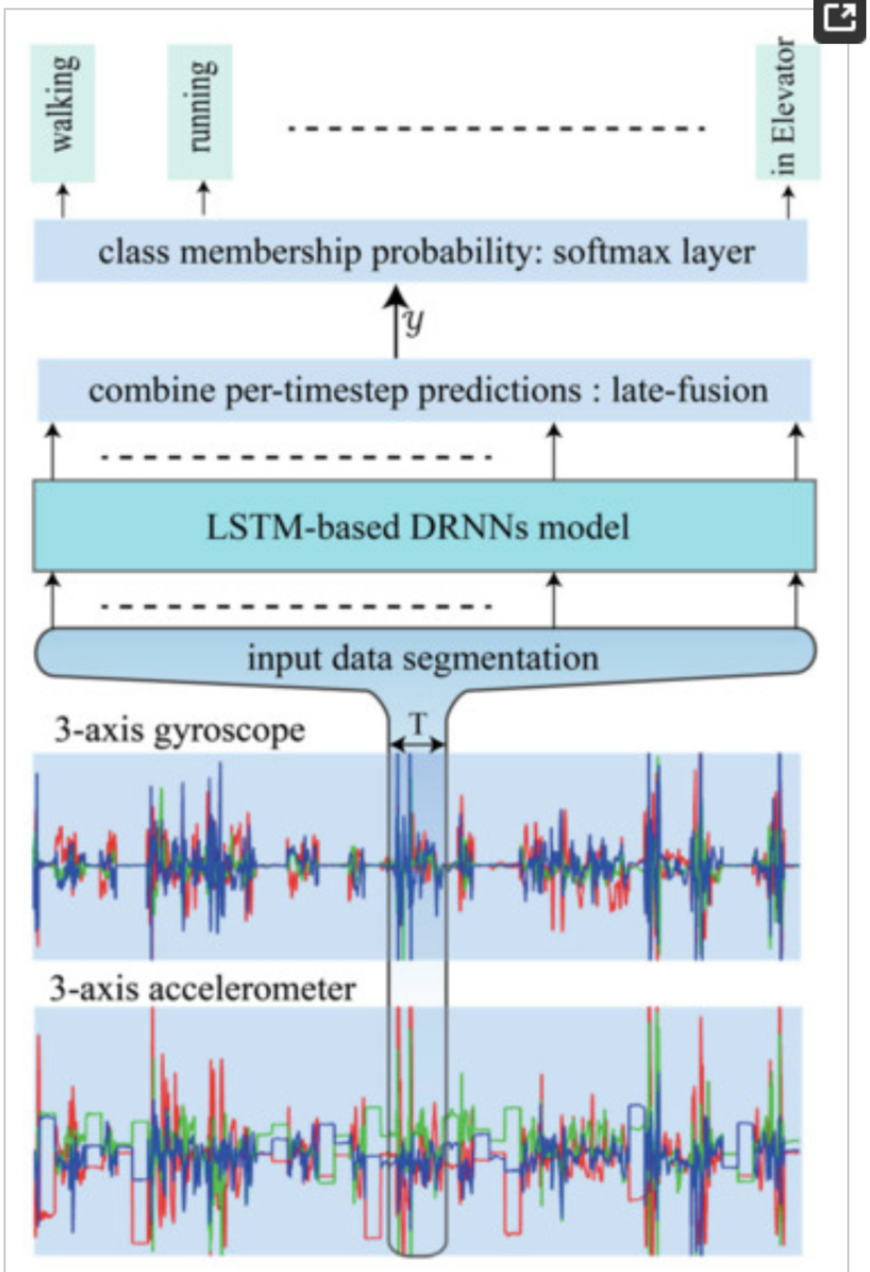
Figure 2.9: Depiction of CNN Model for Accelerometer Data. Taken from Convolutional Neural Networks for Human Activity Recognition using Mobile Sensors.



Long Short-Term Memory networks or LSTMs for short have proven effective in challenging sequence prediction problems when trained at scale for such tasks as handwriting recognition, language modeling, and machine translation. The LSTM learns to map each window of sensor data to an activity, where the observations in the input sequence are read one at a time, where each time step may be comprised of one or more variables (e.g. parallel sequences).

The figure below taken from the paper provides a depiction of the LSTM model followed by fully-connected layers are used to interpret the internal representation of the raw sensor data.

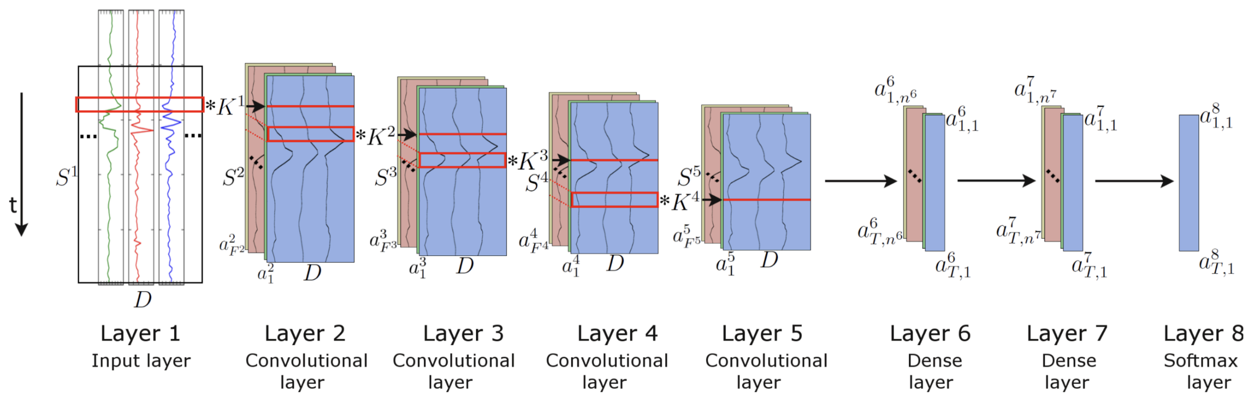
Figure 2.11: LSTM RNN for Activity Recognition. Taken from Deep Recurrent Neural Networks for Human Activity Recognition (Ming & al., 2014).



Deep network architecture is used with four convolutional layers without any pooling layers, followed by two LSTM layers to interpret the extracted features over multiple time steps. The authors claim that removing the pooling layers is a critical part of their model architecture, where the use of pooling layers after the convolutional layers interferes with the convolutional layers' ability to learn to downsample the raw sensor data.

The figure below taken from the paper makes the architecture clearer. Note that layers 6 and 7 in the image are, in fact, LSTM layers.

Figure 2.12: CNN-LSTM Model for Activity Recognition. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition (Ming & al., 2014).



3. STRATEGIES FOR FUTURES TRADING

3.1 Scalping

3.1.1 Characteristics and objectives

Scalping is a trading strategy aimed at profiting from minor price changes in a stock's price. People who implement this strategy are convinced that small stock price moves are more manageable to strategize around than larger ones that can prove challenging to foresee. Such traders like to place from ten to even several hundred trades daily to maximize profit and minimize losses. A large amount of small profits turns into significant profits, especially if a trader using the scalping strategy knows when to use an exit strategy to prevent losses.

Before discussing scalping as a strategy for futures contracts, it is essential to establish the theoretical framework of the scalping strategy, which was first used on the foreign exchange market (Forex) (The forex army, 2019). When deciding whether the Forex scalping strategy is appropriate, one should consider the amount of time available for trading. Scalping on the market requires constant analysis of the market and submission of many orders, which makes it practically a full-time job.

In addition, there are only a few hours during the day when the forex scalping system can be used on the market. A trader must be able to make decisions in a short time. For a forex scalping strategy to bring profits, an investor must quickly anticipate future price movements in the market and open and close positions quickly, sometimes in a fraction of a second.

Herd psychology also has a significant impact on the price movement in the market. An excellent example is the rapid movement of some currencies in the face of Chinese expansion in the early 2000s. During the early 2000s, the Australian dollar (AUD) and the Canadian dollar (CAD) gained nearly 40% against the US dollar. Australia and Canada are exporters of goods, so their currencies grew in value when China enjoyed dynamic economic growth. Many traders took a long position on AUD and CAD in reaction to China's rapid growth (The forex army, 2019).

In addition to the ability to predict short-term movements, investors must have the ability to close positions at a loss quickly. The main task is to make more profitable transactions than the lossy ones and get out of position as soon as possible.

Scalping strategy on the minute chart

The basic idea of scalping is to open many items, which usually last from a few seconds to several minutes. Some of the scalping strategies developed by professionals have gained popularity. For example, Paul Rotter placed orders to buy or sell using the order sheet in making decisions. Rotter traded even a million contracts during the day and developed a legendary reputation among investors. His success inspired many followers. It is essential to build individual setups while studying the strategies that have been developed.

Scalping is one of the more interesting ways to participate in financial markets. Unfortunately, it is just as attractive as it is difficult. Most novice investors often try to merge - they think that the shorter transactions, the easier it is to earn a profit. Nothing could be more wrong. Beginner scalpers are very trigger-happy and often do something that we can describe as "shooting everything that moves" (Investopedia, 2019).

When developed and applied correctly, a professional scalping strategy can be very profitable. There are also individual investors involved in scalping, but often they do not have such technological resources as their colleagues from financial institutions, which reduces their chances of generating a higher profit (although it does not prevent them from achieving it).

Scalping can be a very demanding strategy. In order to generate regular profits from scalping, a trader must first be able to control one's nerves. Unfortunately, Beginner investors practice scalping by generating almost exclusively losses, which leads to a rapid reset of an investment account. With such an investment strategy, everything happens very quickly, which is why a trader must react quickly to changes, both those beneficial for the investor and those that are entirely unfavorable.

Scalping is based on transactions lasting from a few minutes to several seconds. Such a game causes vast stress, which is compounded by a rapid change in the value of the investment account. During scalping, serious problems can be encountered even by people who have been doing it for years.

The advantage of the stock market is that it is easier to learn from the Forex market, which does not mean it is easy overall. There is no financial leverage on the equity market, so during the scalping trade, the value of the account changes much slower. The problem, however, is that the lack of leverage means the need to use vast resources so that ultra-short transactions have a chance to bring a profit high enough that after paying the commission for the brokerage house, it still is profitable. Using the scalping strategy, one only needs to focus on trading on those shares and brokerage houses that offer a relatively low commission for transactions. High commissions will make trading completely unprofitable - commissions will cut into any profit earned (Investopedia, 2019).

x Minute Stocks Scalping strategy

In the x Minute Stocks Scalping strategy, as the name implies, an x-minute (where x is the amount of time between transactions) chart is used. Five technical analysis indicators are used: Exponential Moving Average (EMA), Bollinger Bands, Parabolic SAR, MACD and RSI (Di Lorenzo, 2012, p. 79).

3.1.2 Exponential Moving Average

The EMA used here, is one of the most popular AT indices, calculating the average of a given number of periods including the weights of these periods. It was designed to improve on the idea of a Simple Moving Average (SMA) by giving more weight to the most recent price data. Since the new data carries greater weight, the EMA responds more quickly to price changes that SMA does.

$$EMA=Price(t)\times k+EMA(y)\times(1-k)$$

where:

t today

y yesterday

N number of days in EMA

$k=2\div(N+1)$

Traders sometimes watch moving average ribbons, which plot a large number of moving averages onto a price chart, rather than just one moving average. Though seemingly complex based on the sheer volume of concurrent lines, ribbons are easy to see on charting applications and offer a simple way of visualizing the dynamic relationship between trends in the short, intermediate, and long term.

Traders and analysts rely on moving averages and ribbons to identify turning points, continuations, and overbought/oversold conditions, define support and resistance areas, and measure price trend strengths.

3.1.3 MACD approach

MACD, or Moving Average Convergence Divergence, is calculated as the difference between long-term and short-term exponential average. The MACD indicator consists of two lines - the MACD line, which is calculated as the difference between Slow EMA (medium long term) and Fast EMA (medium short term) and the second line being a simple moving average (Appel, 2005, p. 166).

The prices of all these financial instruments are not moving in a straight line, but rather in a jagged 'up and down' fashion with a series of sharp peaks and troughs. These fluctuations and oscillations are filtered out by low pass filters. A low-pass filter will pass a signal with a frequency that is lower than a selected cutoff frequency and attenuate signals with frequencies higher than this cutoff frequency. The smoother profile presented by MAs allows to analyze and identify underlying trends.

The purpose of the MACD formula is to harness the benefits of two different low-pass filters: a fast EMA and a slow EMA. The typical or "box" setting for the fast EMA is 12 periods; for example, an EMA is calculated over 12 periods. The usual or "box" setting for the slow EMA is 26 periods; for example, an EMA calculated over 26 periods.

Figure 3.1: MACD Trading Guide: What is MACD (CMC Markets, 2020)

The MACD indicator contains of signal lines and a histogram. The histogram displays the difference between the MACD line (often referred to simply as MACD) and the signal line plotted as a bar chart over time. The MACD histograms oscillate above and below a "zero line", where the MACD and the signal line intersect. The shape of the histogram is important; for instance, a rising histogram profile indicates an uptrend. The shape of the histogram with respect to the zero line also has a bearing on the trend, as a strong downtrend is indicated by a falling profile below the zero line.

There are multiple ways the traders can use the MACD. It can be used to generate buy and/or sell signals using crossovers for traders interested only in them. When the MACD crosses the signal line from under it and goes over, a buy signal is generated. Conversely, when the MACD crosses the signal line from above and goes under it, this generates a sell signal. These signals are also referred to as a MACD bearish crossover or a MACD bullish crossover, depending on which way the price heads.

Figure 3.2: MACD Trading Guide: Uptrend Signal (CMC Markets, 2020)

Even though the MACD indicator was developed some time ago, it is still commonly used in today's modern markets due to its effectiveness. One of the core reasons it has remained at the forefront of technical analysis portfolios is its ability to predict potential market direction in conjunction with price action.

The way to do this is by using the concepts of divergence and convergence. The MACD is said to be convergent with price action if both prices and the MACD are moving in the same direction. In other words, if prices are making higher highs (in an uptrend) and the MACD makes corresponding higher highs, then we have convergence. Convergence of the MACD with price action confirms the strength, direction, and momentum of a trend. If the MACD moves in the opposite direction, making lower highs as the price is making higher highs, then we have negative divergence. Divergence with price action indicates the potential weakening or possible reversal of a trend.

Figure 3.3: MACD Trading Guide: Convergence (CMC Markets, 2020)

The MACD signal line is the second component of the MACD indicator. It is an EMA of the MACD over a certain number of periods. The standard or "box" setting for this is nine; in other words, an EMA of the MACD is calculated over nine periods. It is used to generate buy and sell signals as the MACD line crosses.

As the MACD and MACD signal line are derived from two EMAs, their value will be dependent on the underlying security. It is not possible to compare these values for a group of currencies or across markets such as between the US SPX 500 and an exchange-traded fund.

One of the most significant limitations of the MACD is the occurrence of false positives. A reversal is signaled, but never takes place. The opposite can also take place, where a reversal occurs without being signaled. A way to overcome any of these false signals would be to implement a MACD signal line filter. Another drawback is that moving averages slightly lag behind real-time prices. This is because it is an average of the historical prices, so any drastic price changes would not be seen straight away. Therefore, although traders widely use the MACD, it might not be the best technical tool to use in isolation when dealing with volatile price movement.

MACD is widely provided by a majority of execution-only brokerage houses as one of the pre-set free analytical tools. These providers use such tools to entice individual traders to sign up for accounts.

3.1.4 Relative Strength Index

RSI, or Relative Strength Index, is used in both short-term trade - scalping or day trading as well as in medium and long-term trade. Relative Strength Index is responsible for examining the ranges of upward and downward movements - it calculates the average value of the increase in closing prices and the average value of the drop in closing prices, and then the result of these calculations is presented in the chart. The index takes values from 0 to 100.

The RSI is computed with a two-part calculation that starts with the following formula:

$$\boldsymbol{RSI\ one = 100 - [\frac{100}{1 + \frac{Average\ Gain}{Average\ Loss}}]}$$

The average gain or loss used in the calculation is the average percentage gain or loss during a look-back period. The formula uses a positive value for the average loss. Most common is to use 14 periods to calculate the initial RSI value.

Once there are 14 periods of data available, the second part of the RSI formula can be calculated. The second step of the calculation smooths the results.

$$\mathbf{RSI\ two} = \mathbf{100} - \left[\frac{\mathbf{100}}{\mathbf{1} + \dfrac{(\mathbf{Previous\ Average\ Gain} \times \mathbf{13}) + \mathbf{Current\ Gain}}{-((\mathbf{Previous\ Average\ Loss} \times \mathbf{13}) + \mathbf{Current\ loss})}}\right]$$

Figure 3.4: Relative Strength Index: General Electric

It is generally accepted, when the RSI surpasses the horizontal 30 reference level, it is a bullish sign, and when it slides below the horizontal 70 reference level, it is a bearish sign. An investor can interpret that RSI values of 70 or above indicate security is becoming overbought or overvalued and may be primed for a trend reversal or corrective price pullback. An RSI reading of 30 or below indicates an oversold or undervalued condition.

During trends, the RSI readings may fall into a band or range. During an uptrend, the RSI tends to stay above 30 and should frequently hit 70. During a downtrend, it is rare to see the RSI exceed 70, and the indicator frequently hits 30 or below. These guidelines can help determine trend strength and spot potential reversals. For example, if the RSI cannot reach 70 on a number of consecutive price swings during an uptrend but then drops below 30, the trend has weakened and could be reversing lower.

The opposite is valid for a downtrend. If the downtrend is not able to reach 30 or below and then rallies above 70, that downtrend has weakened and could be reversing to the upside. Trend lines and moving averages are helpful tools to include when using the RSI in this way.

A bullish divergence occurs when the RSI creates an oversold reading followed by a higher low that matches correspondingly lower lows in the price. This indicates rising bullish momentum, and a break above oversold territory could be used to trigger a new long position.

A bearish divergence occurs when the RSI creates an overbought reading followed by a lower high that matches corresponding higher highs on the price.

It can be seen from the following chart that a bullish divergence was identified when the RSI formed higher lows as the price formed lower lows. It was a valid signal, but divergences can be rare when a stock is in a stable long-term trend. Using flexible oversold or overbought readings will help identify more potential signals.

Figure 3.5: Relative Strength Index: Bank of America

The RSI compares bullish and bearish price momentum and displays the results in an oscillator that can be placed beneath a price chart. Like most technical indicators, its signals are most reliable when they conform to the long-term trend.

True reversal signals are rare and can be difficult to separate from false alarms. A false positive, for example, would be a bullish crossover followed by a sudden decline in a stock. A false negative would be a situation where there is a bearish crossover, yet the stock suddenly accelerated upward. Similarly to MACD, RSI may not be suitable for futures trading as short term volatility may exceed acceptable risk tolerance (Hari, 2015).

3.1.5 Bollinger Bands

The Bollinger Bands, created by John Bollinger, consist of three lines, and its construction and operation are very simple (Bollinger Bands, 2020). The middle line from the Bollinger bands is a moving average, and the other two lines - one running above and the other below that average, are means shifted to the distance determined by the standard deviation.

Bollinger bands are calculated as follows:

$$BOLU = MA(TP,n) + m * \sigma[TP,n]$$

$$BOLD = MA(TP,n) - m * \sigma[TP,n]$$

where:

BOLU=Upper Bollinger Band

BOLD=Lower Bollinger Band

MA=Moving average

TP (typical price)=(High+Low+Close)÷3

n=Number of days in smoothing period (typically 20)

m=Number of standard deviations (typically 2)

σ[TP,n]=Standard Deviation over last ***n*** periods of TP

Bollinger Bands are a highly popular technique. Many traders believe the closer the prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market. John Bollinger has a set of 22 rules to follow when using the bands as a trading system (Bollinger Bands, 2020).

In the chart depicted below, Bollinger Bands® bracket the 20-day SMA of the stock with an upper and lower band along with the daily movements of the stock's price. Because standard deviation is a measure of volatility, when the markets become more volatile, the bands widen, during less volatile periods, the bands contract.

Figure 3.6: Bollinger Bands (Fidelity , 2020)

The squeeze is the central concept of Bollinger Bands. When the bands come close together, constricting the moving average, it is called a squeeze. A squeeze signals a period of low volatility and is considered by traders to be a potential sign of future increased volatility and possible trading opportunities. Conversely, the wider apart the bands move, the more likely the chance of a decrease in volatility and the greater the possibility of exiting a trade. However, these conditions are not trading signals. The bands give no indication when the change may take place or in which direction price could move.

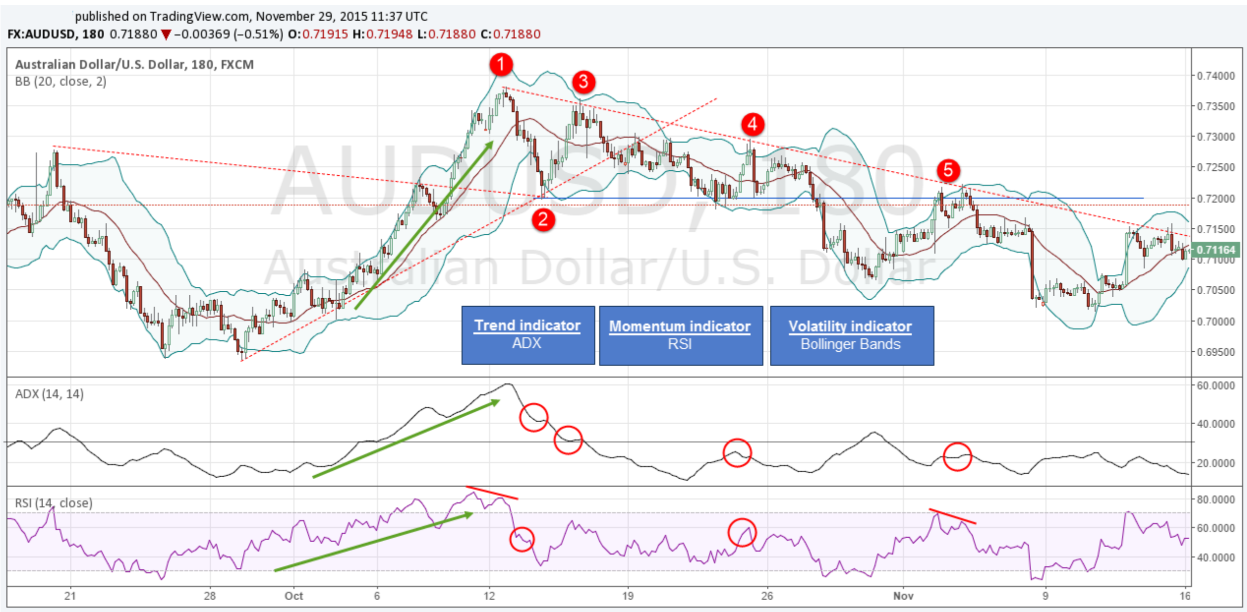
Bollinger Bands are not a standalone trading system. They are simply one indicator designed to provide traders with information regarding price volatility (Grimes, 2012). John Bollinger suggests using them with two or three other non-correlated indicators that provide more direct market signals. He believes it is crucial to use indicators based on different types of data.

Some of his favored technical techniques are moving average divergence/convergence (MACD), on-balance volume and relative strength index (RSI).

3.1.6 Parabolic SAR

Finally, parabolic SAR is a parabola consisting of a row of dots located above or below the price chart. Examples of these tools are shown in the graphs below:

Figure 3.7: Parabolic SAR (tradeciety, 2020)



Also known as parabolic stop and reverse, Parabolic SAR is a technical indicator developed by J. Welles Wilder Jr (fxpro, 2020). It is used in trending markets in order to determine entry and exit points as well as to set effective trailing stop-loss parameters. Parabolic SAR is presented as a series of dots, plotted either over or under the current market price. The simplest way to read this indicator is to sell when the price is below the Parabolic SAR and to buy when the price is above it.

It calculates the value of the following period through using the current period added to an acceleration factor (normally valued at 0.02 and increased by a further 0.02 each time a new extreme high or low point is registered) which is multiplied by the value of the last registered Extreme Point (EP) minus the current value. For this reason, the acceleration factor causes SAR to converge on the current price as a trend continues. This indicator takes as given that trends tend to be short-lived and can only continue unabated for a limited period of time.

Next figure shows an example trades placed by the application of multiply technical indicators described above together.

Figure 3.8: Example of tools used in a scalping strategy (Learn Forex Trading, 2020)

3.2. Day Trading

3.2.1 Characteristics and Objectives

Day trading is an investment method consisting of buying and selling securities during one trading session. It means, in other words, a one-day investment, which is a type of short-term investment.

The investor closes and opens the position in the same trading session. When the opening of an item extends to the next day, it is no longer a one-day transaction. At any time during the session, transactions are allowed, but all items must be closed by the end of the day (Gannon, 2010, p. 23).

Investors speculating on shares have the option of using financial leverage of 2: 1, and on a day trading of 4: 1. This means that in one-day transactions, the capital maybe even four times smaller. According to a study from 2014, one in five traders invested on the stock exchange on a day trading basis (Investopedia, 2019).

Benefits of one-session investing

"One-session investing allows investors to use their capital to the maximum because it does not require holding a hedge against inter-sessional price changes" (Bernsten, 2010, p. 105). Most brokerage houses enable active one-day investing, assuming that they have adequate capital and are sufficiently mature and responsible. If the broker believes that the positions opened by the investor do not entail significant losses, it allows him or her to open more positions on the markets without the necessity to pay high deposits.

The one-day investing method means that the investor suffers a much lower risk of loss than during a positional game. Thanks to day trading, investors are much less affected by price changes, which are reactions to news and situations after closing the session.

Objectives of a Day-Trading strategy

Day Trading is characterized by extremely precise rules regarding all aspects of transactions. The most important feature of Day Trading is the already mentioned approach that virtually prohibits leaving open positions overnight (Gannon, 2010, p. 244). It is considered that the volatility prevailing in the night markets is too low and unpredictable; therefore day traders only trade in periods of the highest liquidity during the day.

Opening positions

Opening positions should be done mainly in moments of the highest volatility, i.e:

• at the opening of the London session

• at the opening of the New York session

On the other hand, the position is opened only based on precisely defined rules selected from the formations described above. Behind the sense of each of them is the universal approach for day trading, saying that it is best to follow the market movements caused by the most prominent players. Of particular importance here is the implementation of potential Stop Loss orders. Positions have to be opened with clearly defined Stop Loss and Take Profits (Gannon, 2010, p. 250).

3.2.2 Using signals to enter positions

It is paramount for all day traders to establish rules for setting Stop Loss and Take Profit orders (Artemov, 2019). A Stop Loss (SL) is a protective order that limits possible losses of the trader in an open position. It automatically closes the trade when a certain level or amount of losses is reached. A Stop Loss is placed either to limit losses or to lock in profit. In the latter case the order is placed in the profitable area.

A Take Profit (TP) is an order locking in profit without the trader's participation. The order automatically closes the trade when the price reaches a certain level.

Both Stop Loss and Take Profit must be placed in accordance with the trader's strategy. For trading to be stable and successful, these orders are obligatory. The Stop Loss minimizes losses and enhances risk management.

Almost all trading strategies include the use of a Stop Loss and/or a Take Profit. Each trader has their criteria of money management (MM) that tell them how much they can afford to lose in each trade. The overarching trading strategy dictates where to place an SL and a TP.

Another advantage is that it is much easier to develop systems and methods for one-day transactions than for those that are long-term. Information on the profit or loss of a given transaction is known more quickly than in long-term investments. It is an opportunity for the investor to learn from his own mistakes and acquire the skills to invest appropriately.

Momentum Indicator (MOM)

The Momentum Indicator is useful when concluding transactions in day trading. It indicates the degree of price change. If the momentum decreases quickly, it means a quick reduction of prices and their significant changes in the given sessions. However, when the momentum value suddenly increases, the market is in an upward trend. When the MOM changes from negative values to positive values, there is a high probability of an upward trend. In the other case, it can be assumed that prices will go down. To calculate the one-day momentum, subtract today's price from yesterday. For example, if today's price is USD 65 and yesterday USD 63, today's one-day momentum will be +2 (Bernsten, 2010, p. 107).

An investor who uses this method should actively participate in the market and frequently monitor prices. Active markets where the price changes are significant are best to apply this method. To make the most of it, one has to invest in several contracts. This method involves drawing and controlling charts of 5-minute closing prices from the first two hours of any market session. These are the final prices. They should not be confused with maximum or minimum. This method can give a buy and sell signal in one day, but another possibility is the lack of any signal (Bernsten, 2010, p. 197).

In the USA, investors who are involved in day trading must meet set requirements. To be classified as a day trader, three transactions must be made within five business days. They must start and end in one session. This will also happen when the number of one-day transactions is 6 per cent of all transactions in a given period. The value of the account of a person who engages in day trading must be at least $ 25,000. If this value drops below this amount, brokers prevent one-day transactions from being executed for a further 90 days or until the account balance returns to USD 25,000 (Bernsten, 2010, p. 198).

Day Trading is somehow an evolution of the concept of the above-described scalping. A large part of the assumptions remains unchanged here while the time horizon of the investment changes. By investing on the basis of Day Trading, each transaction is concluded within one day to exit all open positions before after-hours trading, when the liquidity of the markets is lower. Most commonly, positions remain open between 30 minutes to 2 hours.

3.3 Swing Trading

3.3.1 Characteristics and Objectives

The opposite of the methods mentioned above is Swing Trading. By investing following this approach, the investor deliberately leaves transactions open on the account for more than a day, sometimes much longer (sometimes even several weeks). Swing Trading assumes using "swings", i.e. clearly marked sections on the chart. In principle, it is instead used with higher intervals such as daily or weekly. Others are capital management principles, Stop Loss and Take Profit methods.

Detailed characteristic of Day Trading

Day Trading is, in fact, a very extensive strategy, inside which we can distinguish many interesting sub-strategies that are stand-alone methods of approaching the market. It creates countless possibilities on which traders can build their strategy. One of the more well-known promoters of Day Trading is the American investor Joe Ross. In his many works, traders can find an extensive range of formations characteristic of Day Trading. These include, among others (Ross, 2004, p. 44):

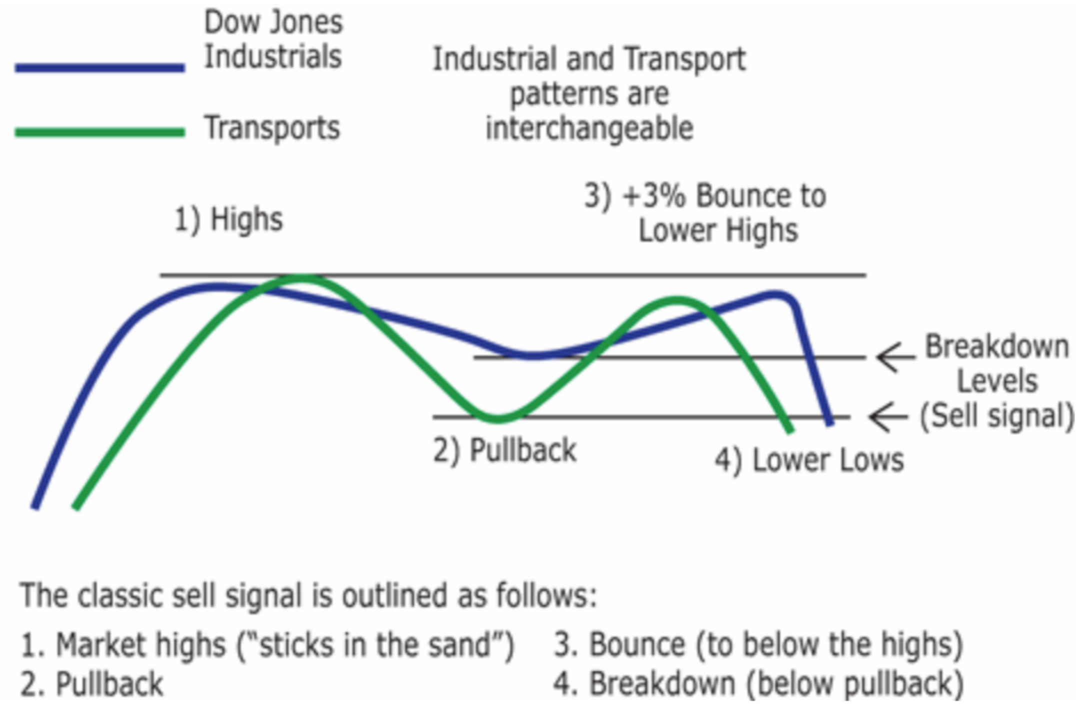
- Ross' Hooks
- 1-2-3 Formation
- Ledge Formation
- Inside Bar
- Outside Bar
- Reversal Pattern
- Trader’s Trick Entry (TTE)

It is important to explain at least some of the notions listed above.

3.3.2 Using signals for entering positions

According to Dow Theory, a classical technique based on the recognition of higher highs and lows can be used to determine the direction. The Dow theory is a financial theory that says the market is in an upward trend if one of its average’s advances above a previous important high and is accompanied or followed by a similar advance in the other average. For example, if the Dow Jones Industrial Average (DJIA) climbs to an intermediate high, the Dow Jones Transportation Average (DJTA) is expected to follow suit within a reasonable period of time (TheDowTheory.com, 2019).

Figure 3.9: Dow Theory Signal



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According to the Dow Theory, a reversal in the primary trend is signaled when the market is not able to create another successive peak and trough in the direction of the primary trend. For an uptrend, a reversal would be signaled by an inability to reach a new high followed by the inability to reach a higher low. In this situation, the market has gone from series of successively higher highs and lows to successively lower highs and lows, which are the components of a downward primary trend (Schannep, 2008).

The reversal of a downward primary trend occurs when the market no longer falls to lower lows and highs. It happens when the market establishes a peak that is higher than the previous peak, followed by a trough that is higher than the previous trough, which are the components of an upward trend

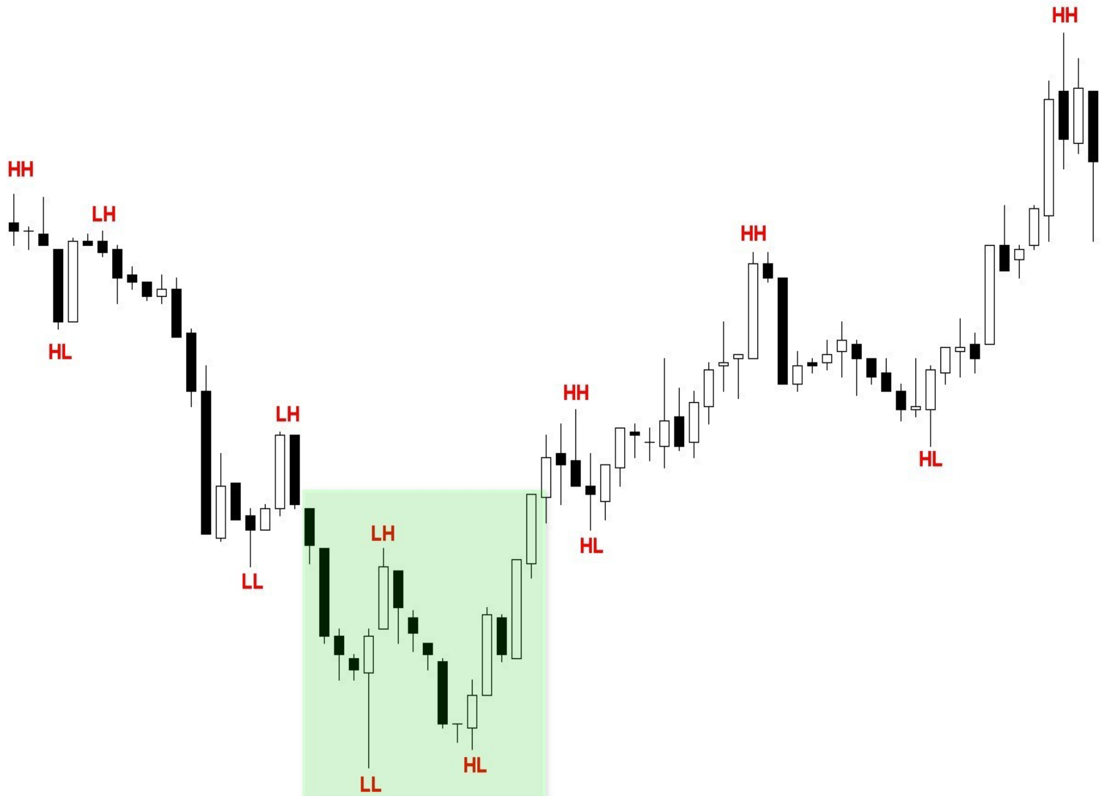
By Joe Ross, the natural support and resistance points are the places on the chart where the price corrects and moves along with the trend. For an uptrend, these are the new local lows emerging after a correction. For a downtrend, these are the new local highs after each correction. These levels almost coincide with the RRH points. SL is put behind these levels.

On this basis, the trend changes from downward to upward when sellers lose their "strength" and cannot break a new low. The same is true for a downtrend (forexclub, 2020).

Figure 3.10: Ross Hooks – Example 1

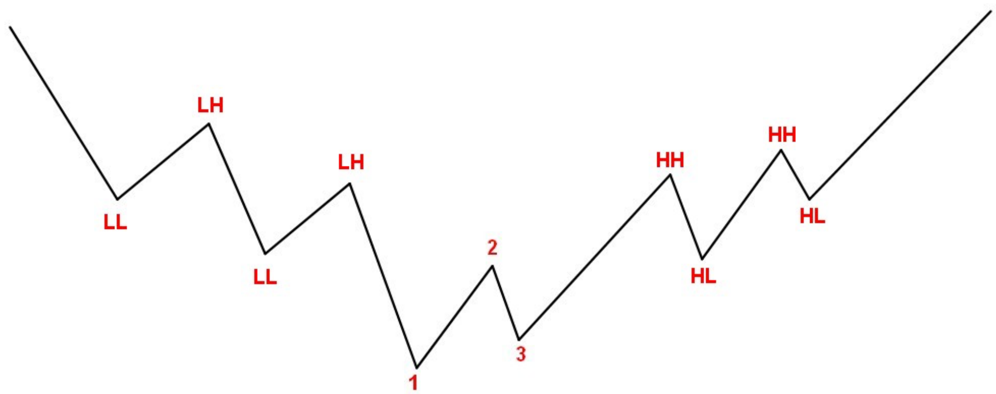
When the trend loses its "strength", sellers can no longer establish a new low, which can be seen in the chart below:

Figure 3.11: Ross Hooks – Example 2



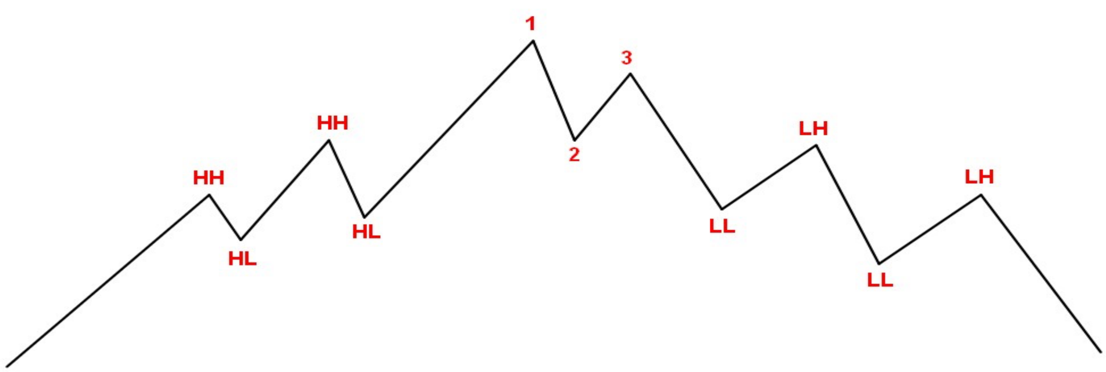
The green rectangle shows one of several layouts on which the Ross Hook concept is based. Another attempt to attack the sellers at the previous minimum fails, which results in the creation of the so-called 1-2-3 formation (Sperandeo, 1993). This structure is nothing else than the proper formation of individual lows and highs (LL, LH, HL) or highs and lows (HH, HL, LH) (Ross, 2004, p. 58). The following simplified diagram makes the shape of this structure clearly visible:

Figure 3.12: Ross Hooks – Example 3



The above pattern is the first signal that the market can change its current course and start moving north. Obviously, a structure in which the appropriate arrangement of highs and lows promises to increase. The following is the opposite of this pattern, which will naturally predict decreases, which can be seen in the figure below:

Figure 3.13: Ross Hooks – Example 4



Formation negation takes place at the time of breaking down the so-called 1 or establishing a lower low or a higher high through point 3. Formation 1-2-3 is easy to identify and can be found at any time interval. Both traders using scalping as well as long-term investors can use it to look for momentum on the price chart to take the position along with the newly developing market movement. In itself, it is not only an appropriate structure composed of highs and lows but also a very good indicator to enter a market that maintains an appropriate profit-risk ratio. Many investors base their strategies on the 1-2-3 model. However, it is important to remember that traders should always look for this scenario when the market is in an upward or downward trend. The next step after correctly determining the 1-2-3 structure is to find the Ross' Hook formation. It is pretty simple and very objective because it is the candle that indicates the 1-2-3 system and creates a new local maximum or minimum. After that, there should be a correction made by at least one candle with lower or higher prices: maximum and minimum. It is precisely the moment drawn on the diagram, with the Ross' Hook shown by the green rectangle:

Figure 3.14: Ross Hooks – Example 5

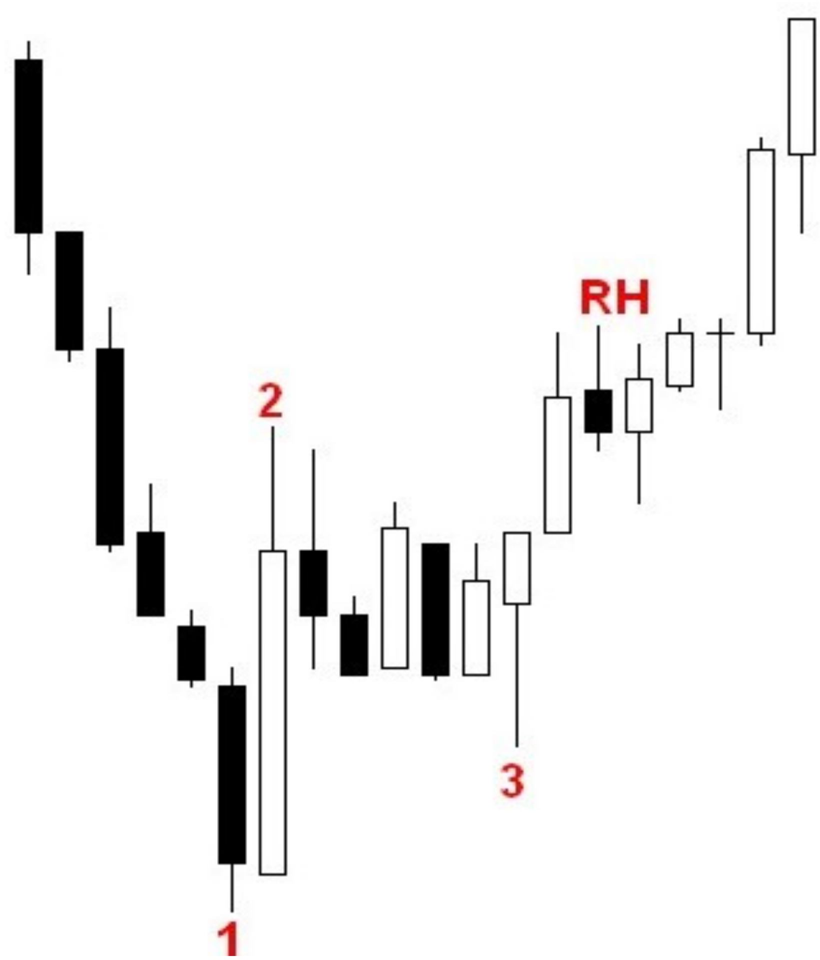
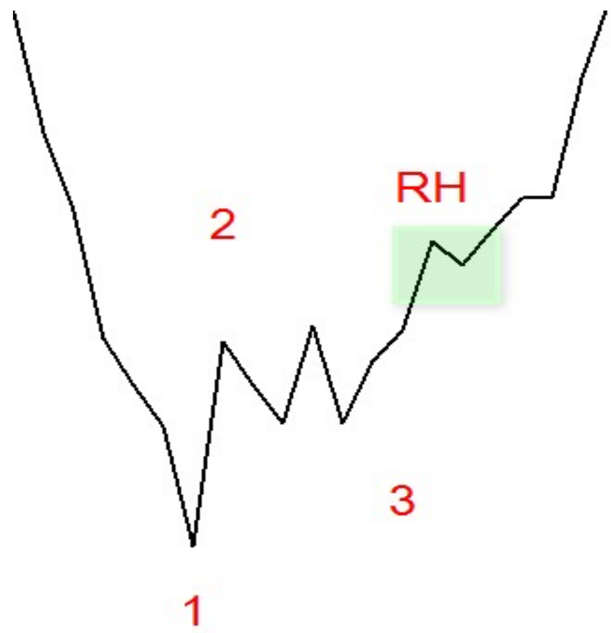
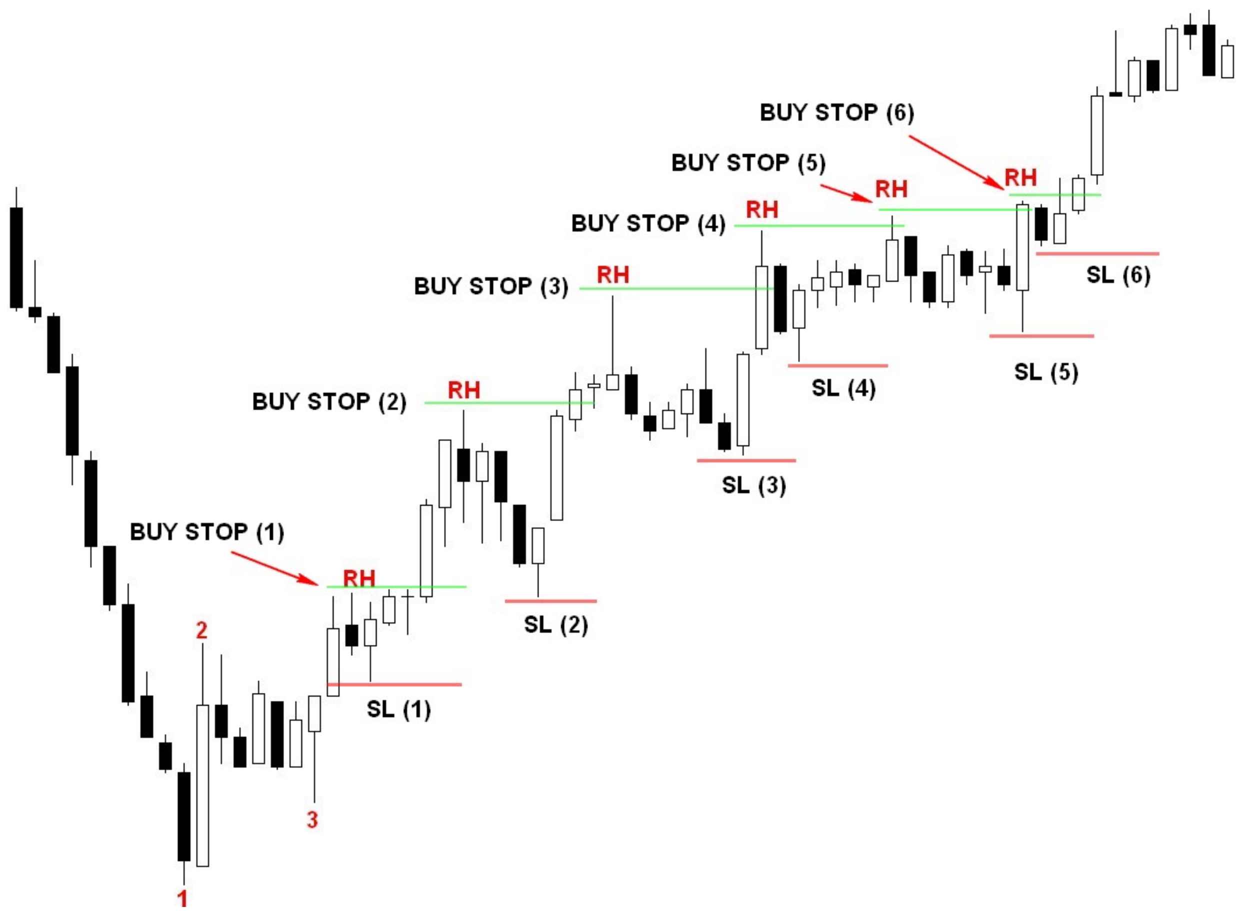


Figure 3.15: Ross Hooks – Example 6



Investing using Ross' Hooks in the simplest terms assumes their regular appearance and joining the market following the prevailing trend (Ross, 2004, p. 78). Using Ross' Hooks is a comprehensive strategy because traders do not immediately enter the market but set up a "barbed wire" secured by an SL order below or above the bottom of the last correction and wait for the effect of the price (Forex Trading Resources, 2012). If traders come across when the market ends its trend, then the position should not be opened. However, if the trend on the chart continues, traders can conduct their position in the right way by, for example, moving the SL order into ever higher lows or over ever lower highs. There are many possibilities to run a position, and experience plays a significant role in determining the appropriate course of action. As seen in the chart below, if market behavior is interpreted correctly, traders can participate relatively simply in the long position or use this knowledge to pyramid into a position.

Figure 3.16: Ross Hooks – Buy and Sell Orders



If a trader interprets the 1-2-3 formation too late or finds an appropriate moment on the chart, then the system assumes that one can join the rest of the traders participating in the trend after Ross' Hooks appear. As presented in the example above, Ross' Hooks occurred quite often, which allowed many moments to use this to play on highs. A few ticks above each hook marked RH; there is a green line indicating where the Buy Stop order was placed and a red line placed under the last low of the Stop Loss order. Ross' Hooks are an ideal tool for traders who focus only on the price graph in each time interval. It is a solid foundation to build an advanced strategy that generates regular profits. In addition, almost every investor using Ross' Hooks should interpret any given chart in the same way, which makes it a handy tool. Of course, like any method, it is not perfect, and one should be aware of false positives that may occur at any time. Nevertheless, this strategy enjoys decent efficiency and is a staple in the arsenal of a day-trader (Ross, 2004, p. 101).

3.3.3 Managing positions

The following clear and rigid rules are also important when managing the position in Day Trading:

- As soon as possible, we set Stop-Loss to break even
- we use the time limit Stop-Loss characteristic of a specific formation
- part of the position is closed on the first Take Profit level, subsequent parts of the position on the following TP levels

Closing positions

Closing positions in Day Trading takes place through:

- activation of the Stop Loss order defined as mandatory when opening transactions
- time-based stop-losses (e.g. after 5 candles without effect)
- emergency manual closing of the position in the face of essential data readings
- closing positions on subsequent Take Profit levels (Ross, 2004, p. 199)

Day Trading entails almost an infinite amount of strategies, concepts, and possible formations. It is hard to describe in detail all the possible ways a day-trader can generate profit on the market. Regardless of whether someone is a beginner trader or is already successfully investing in the financial markets, Day Trading can be a big part of any strategy. It has simple, clearly defined rules with a high skill ceiling that makes it a concept suitable both for beginners and experts. In addition, it can provide excellent results if used correctly (Ross, 2004).

Managing unrealized profits and losses of futures positions held over multiple days

Managing unrealized profits from futures positions held over multiple trading sessions is different from managing day trading positions. Intraday risk becomes less important and can be regarded as noise on the underlying daily price trend.

The risks when getting out of an existing position can be:

- Giving up too much of unrealized profits
- Incurring too much of an unrealized loss

The main objective of any trader, therefore, becomes to define and manage "too much" in the above. An unrealized profit or loss arises during the life of a trade, reflecting the difference between the current price and the entry price. As soon as the trade is liquidated, the unrealized profit or loss is converted into a realized profit or loss.

An equity reduction or “drawdown” results from a reduction in the unrealized profit or an increase in the unrealized loss on a trade. When confronted with an equity drawdown on a trade in progress, a trader must choose between two conflicting courses of action: (a) liquidating the trade with a view to conserving capital or (b) continuing with it in the hope of making good on the drawdown. Liquidating a profitable trade at the slightest sign of a drawdown will prevent further evaporation of unrealized profits. However, by exiting the trade, the trader is forgoing the opportunity to earn any additional profits on the trade. Similarly, an unrealized loss might be recouped by continuing with the trade instead of being converted into a realized loss upon liquidation. However, if the trade continues to deteriorate, the unrealized loss could multiply. The aim is to be mindful of equity drawdowns while simultaneously minimizing the probability of erroneously short-circuiting a trade. While there are no cut-and-dried formulas to resolve the problem, we will present a series of credible solutions.

Balsara (Balsara, 1992) suggests five approaches to setting stop-loss orders:

1. Visual approach to setting stops

One way of deciding on a stop-loss point for a trade is to be mindful of clues offered by the commodity price chart in question. A chart pattern that signals a reversal formation will also let the trader know precisely when the pattern is no longer valid. Another commonly used technique is to set a buy stop to liquidate a short sale just above an area of price resistance. Similarly, a sell stop to liquidate a long trade could be set below an area of price support. Prices are said to encounter resistance if they cannot overcome a previous high. Similarly, prices are considered to find support if they have difficulty falling below a previous low. Support or resistance is much stronger if prices fail to take out a previous high or low on repeated tries.

2. Volatility stops

The volatility stop acknowledges the fact that there is a great deal of randomness in price behavior, although the market may be trending in a particular direction. Essentially, volatility stops seek to distinguish between minor or random fluctuations and a fundamental shift in the trend. This section discusses some of the more commonly used techniques that seek to make this distinction. Ideally, a trader would want to know the future volatility of a commodity to distinguish accurately between random and nonrandom price movements. However, since it is impossible to know the future volatility, this number must be estimated. Historic volatility is often used as an estimate of the future, especially when the future is not expected to vary significantly from the past. However, if significant changes in market conditions are anticipated, the trader might be uncomfortable using historic volatility. One commonly used alternative is to derive the theoretical futures volatility from the quoted price on an associated option, assuming that the option is fairly valued. This volatility estimate is also known as the implied volatility since it is the value implicit in the current option premium.

In a strictly statistical sense, historical volatility is a one standard deviation price change, expressed in percentage terms, over a calendar year. The assumption is that the per cent changes in a commodity's prices, as opposed to absolute dollar changes, are normally distributed. The assumption of normality implies that the percentage price change distribution is bell-shaped, with the current price representing the mean of the distribution at the center of the bell. A normal distribution is symmetrical around the mean, enabling us to arrive at probability estimates of the future price of the commodity. For example, if cocoa is currently trading at $1000 a metric ton and the historic volatility is 25 per cent, cocoa could be trading anywhere between $750 and $1250 ($1000 * 1 x 25 per cent x $1000) a year from today approximately 68 per cent of the time. More broadly, cocoa could be trading between $250 and $1750 ($1000 * 3 x 25 per cent x $1000) one year from now, approximately 99 per cent of the time. In order to compute the historic volatility, the trader must decide on how far back in time he wishes to go. He or she would want to go as far back as is necessary to get an accurate picture of future market conditions. Accordingly, the period might vary from two weeks to, say, 12 months. Typically, daily close price changes are used for computing volatility estimates. Since a trader's horizon is likely to be shorter than one year, the annualized volatility estimate must be modified to acknowledge this fact. Assume that there are 250 trading days in a year and that a trader wishes to estimate the volatility over the next it days. In order to do this, the trader would divide the annualized volatility estimate by the squareroot of 250/n.

Continuing with our cocoa example, assume that the trader was interested in estimating the volatility over the next week or five trading days. In this case, IZ is 5, and the volatility discount factor would be computed as follows:

$$\textit{Discount Factor} = \sqrt{250/5} = 7.07$$

$$\textit{Volatility over next 5 days} = \frac{0.25}{7.07} = \textit{0.03536 or 3.536\%}$$

The dollar equivalent of this one-standard-deviation percentage price change over the next five days is simply the product of the current price of cocoa times the percentage. Therefore, the dollar value of the volatility expected over the next five days is

$$\$1000 \text{ x } 0.03536 = \$35.36$$

Consequently, there is a 68 percent chance that prices could fluctuate between $1035.36 and $964.64 ($1000 $\pm 1 \times$ $35.36) over the next five days. There is a 99 percent chance that prices could fluctuate between $1106.08 and $893.92 ($1000 2 3 x $35.36) within the same period. The definition of price used in the foregoing calculations needs to be clarified for certain interest rate futures, for example, Eurodollars and Treasury bills, which are quoted as a percentage of a base value of 100. The interest rate on Treasury bills is arrived at by deducting the currently quoted price from 100. Therefore, if Treasury bills futures were currently quoted at 94.45, the corresponding interest rate would be 5.55 percent (100 - 94.45). Volatility calculations will be carried out using this value of the interest rate rather than on the futures price of 94.45.

Using The True Range as a Measure of Historical Volatility

The range of prices gives a nontechnical measure of historical volatility during a trading interval, typically a day or a week. The range of prices represents the difference between the high and the low for a given trading interval. Should the current day's range lie beyond the range of the previous day (a phenomenon referred to as a "gap day"), the current day's range must include the distance between today's range and yesterday's close. It is commonly referred to as the true range. The true range for a gap-down day is the difference between the previous day's settlement price and today's low. Similarly, the true range for a gap-up day is the difference between today's high and the previous day's settlement price.

A tick is the smallest increment by which prices can move in a given futures market. A tick value corresponding to 10 percent signifies that only 10 percent of all observations in our sample had a range equal to or less than this number. In other words, the true range exceeded this number for 90 percent of the observations studied. Similarly, a value corresponding to 90 percent implies that the range exceeded this value only 10 percent of the time. Therefore, a stop equal to the 10 percent range value is far more likely to be hit by random price action than is a stop equal to the 90 percent value.

Instead of concentrating on the true range for a day or a week, a trader might be more comfortable working with the average true range over the past N trading sessions, where N is any number found to be most effective through back-testing. The belief is that the range for the past N periods is a more reliable indicator of volatility as compared to the range for the immediately preceding trading session. An example would be calculating the average range over the past 15 trading sessions and using this estimate to set stop prices. A slightly modified approach recommends working with a fraction or multiple of the volatility estimate. For example, a trader might want to set his stop equal to 150 percent of the average true range for the past N trading sessions. The supposition is that the fraction or multiple enhances the effectiveness of the stop.

Implied Volatility

The implied volatility of a futures contract is the volatility derived from the price of an associated option. Implied volatility estimates are particularly useful in turbulent markets when historical volatility measures are inaccurate reflectors of the future. The theoretical price of an option is given by an options pricing model, as, for example, the Black-Scholes model. The following five data items determine the theoretical price of an option on a futures contract:

1. The current futures price
2. The strike or exercise price of the option
3. The time to expiration
4. The prevailing risk-free interest rate, and
5. The volatility of the underlying futures contract.

Assuming that options are fairly valued, we can say that the current option price matches its theoretical value given by the options pricing model. Using the current price of the option as a given and plugging in values for items 1 to 4 in the theoretical options pricing model, we can solve backwards for item 5, the volatility of the futures contract. This is the implied volatility, or the volatility implicit in the current price of the option. The implied volatility estimate is expressed as a percentage and represents a one-standard-deviation price change over a calendar year. The trader can use the procedure just outlined for historical volatility computations to derive the likely variability in prices over an interval of time shorter than a year.

3. Time stops

Instead of working with a volatility stop, a trader might want to base stops on price action over a fixed interval of time. A trader who has bought a commodity would want to set a sell stop below the low of the past n trading sessions, where *N* is the number found most effective in back-testing over a historical time period. A trader who has short-sold the commodity would set a buy stop above the high of the past *N* trading sessions.

For example, a lo-day rule would specify that a sell-stop be set just under the low of the preceding ten days and that a buy stop would be set just above the high of the preceding ten days. The logic is that if a commodity has not traded beyond a certain price over the past N days, there is little likelihood it will do so now, barring a change in the trend. The value of II may be determined by a visual examination of price charts or through back-testing of data.

Babcock (Babcock, 1989) presents a slight variation for setting time stops, which he terms a “prove-it-or-lose-it” stop.’ This stop recommends liquidation of a trade that is not profitable after a certain number of days, n, to be prespecified by the trader. The idea is that if a trade is going to be profitable, it should “prove” itself over the first N days. If it stagnates within this time frame, the trader would be well advised to look for alternative opportunities.

There should be a mechanism to safeguard against unnecessary losses in the interim period while the trade is left to prove itself. Therefore, the "prove-it-or-lose-it" stop is best used in conjunction with another stop designed to prevent losses from getting out of control.

4. Dollar-value stops

Some traders prefer to set stops in terms of the dollar amount they are willing to risk on a trade. Often, this dollar risk is arrived at as a percentage of available trading capital or the initial margin required for the commodity. If the permissible risk is expressed as a percentage of capital, this would entail using the same money management stop across all commodities. It may not be appropriate if the volatility of the markets traded is vastly different.

For example, a $500 stop would allow for an adverse move of 10 cents in corn, whereas it would only allow for a l-index-point adverse move in the S&P 500 index futures. The stop for corn is reasonable since it allows for normally expected random fluctuations. However, the stop for the S&P 500 is simply too tight. This is the problem with money management stops fixed as a percentage of capital. In order to overcome this problem, the money management stop is often set as a percentage of the initial margin for the commodity. The logic is that the higher the volatility, the greater the required margin for the commodity. This translates into a larger dollar stop for the more volatile commodities.

The dollar amount of the money management stop is translated into a stop-loss price using the following formula:

$$\boldsymbol{Stop - loss\ price\ =\ Entry\ price\ \pm\ Tick\ value\ of\ permissible\ dollar\ loss}$$

Assume that the margin for soybeans is $1000 and that the trader Wishes to risk a maximum of 50 percent of the initial margin, or $500 per contract. This translates into a stop-loss price 40 ticks or 10 cents from the entry price, given that each soybean tick is worth $ cent per bushel. For two contracts, the dollar risk under this rule translates into $1000; for five contracts, the risk is $2500; for 10 contracts, the risk escalates to $5000.

A percentile distribution of daily and weekly true ranges in ticks helps the trader place the money management stop in perspective. For example, the daily analysis for soybeans reveals that 60 percent of the days had a true range less than or equal to 42 ticks. Therefore, there is approximately a 40 percent chance of the daily true range exceeding a 40-tick money management stop.

5. Probability stops, based on an analysis of the unrealized loss patterns on completed profitable trades

A trader could undertake an analysis of the maximum unrealized loss or equity drawdown suffered during the course of each profitable trade completed over a historical time period, with a view to identifying distinctive patterns. If a pattern does exist, it could be used to formulate appropriate drawdown cutoff rules for future trades. Such approach assumes that the larger the unrealized loss, the lower the likelihood of the trade ending on a profitable note.

3.3. Trader and investor strategies

3.3.1 Foundations of options

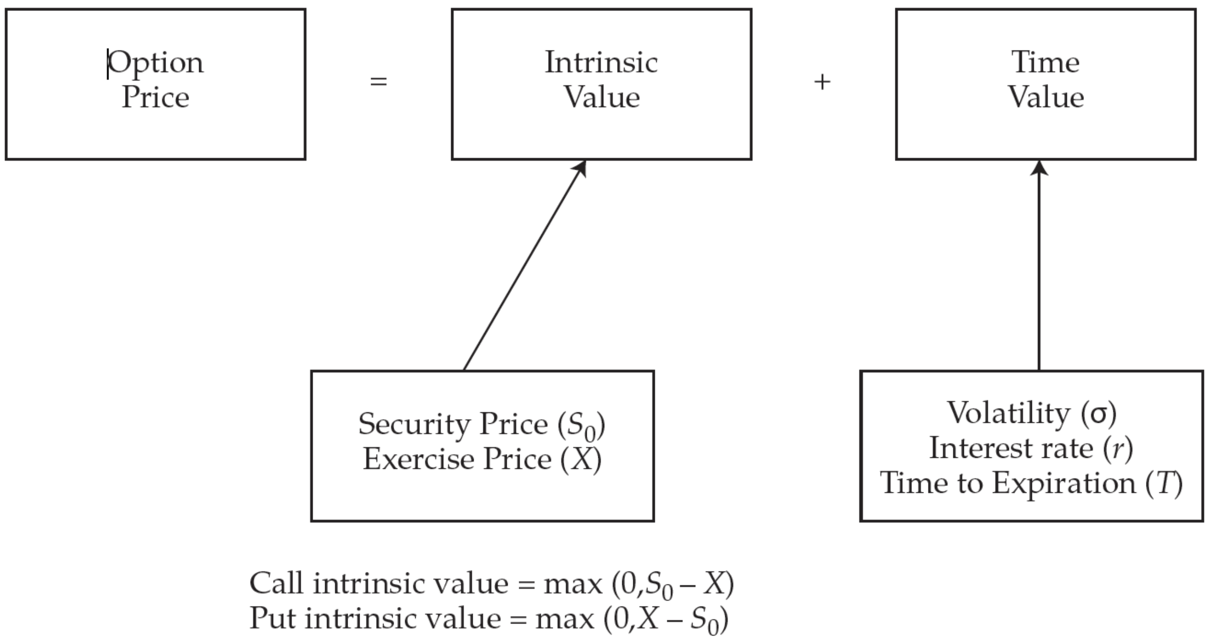
The two basic types of options are *call* options and *put* options (Clarke et al., 2013). A call option provides the owner the right to buy a security at a specified price within a specified period of time. For example, a call option on the S&P 500 Index gives an investor the right to buy units of the S&P 500 at a set price within a specified amount of time. In contrast, the put option gives the owner the right to sell a security at a specified price during a defined interval of time. The right, rather than obligation, to buy or sell the underlying security is what differentiates options from futures contracts. In other words, the option holder has the right to buy or not to buy, to sell or not to sell, depending on which course of action the holder deems most advantageous (Clarke et al., 2013).

In addition to buying an option, investors may sell a call or put option they have not previously purchased, which is called *writing an option*. Understanding bahaviour of put and call option prices and how these basic option positions affect an overall portfolio is critical to developinging complex option strategies.

Options have several important characteristics, including the *strike* or *exercise price* specified in the option contract. The exercise price is the value at which the investor can purchase (with a call option) or sell (with a put option) the underlying security. The exercise price of a simple option is fixed until expiration, whereas the market price of the underlying asset naturally fluctuates.

Moneyness refers to the relationship between the current price of the underlying security and the option's exercise price. Specifically, for call options, the terms *in the money*, *at the money*, and *out of the money* identify whether the underlying security price is currently above, at, or below the option's strike or exercise price, respectively. For example, a call option that has a strike price of $100 when the security price is $120 is in the money because the holder of the option can buy the security for less than its current value. For a put option, the terms in the money, at the money, and out of the money are reversed; they identify whether the underlying security price is currently below, at, or above the option's exercise price, respectively. For example, a put option with a strike price of $100 while the security is priced at $90 is in the money because the investor can sell the security for more than its market price. In either case, an in-the-money option is one that currently has a positive exercise value. A second important characteristic is the *maturity* of the option contract, which defines the time period within which the investor can buy or sell the underlying security at the exercise price. After that date, the option expires and can no longer be exercised. Option contracts come in two general types, or *styles*—those that can be exercised any time up to and including the exercise date and those that can be exercised only on the specific maturity date. An option that can be exercised early is called an *American option*, whereas an option that can be exercised only on the maturity date is called a *European option*. Although this terminology originated within a geographical context, the style terms are now used independently of where the option market is located. For example, most of the options traded on organized exchanges in the United States are American-style options, although a few European-style options are traded in the United States. Another contract specification has to do with adjustments for any dividends or interest paid on the underlying security. An option with a strike or exercise price that is adjusted for cash distributions is called an option with *payout protection*. Option contracts for futures do not have these specifications, however their distinguishing characteristic is that underlying securities – futures expire themselves. That makes it impossible for an option to expire after the underlying future. The price that an exchange-traded option currently trades at, sometimes called the option’s *premium*, depends on a number of factors, including the difference between the contract's strike price and the price of the underlying security. In fact, analysts have come to think of the option's market price as consisting of two distinct parts—the *intrinsic value* and the *time value*—as illustrated below.

Figure 3.17: Components of Option Price



The intrinsic, or exercise, value of a call option is the amount of money that would be received in case when an investor decides to exercise the option to purchase the underlying security at the exercise price and then immediately sells the security at the current market price. Alternatively stated, the intrinsic value is dependent on the relationship between the current security price, S_0, and the exercise price of the option, X. If $S_0 - X$ is positive, then the call option is said to be in the money and has a positive intrinsic value. If $S_0 - X$ is negative, the call option is said to be out of the money and has zero intrinsic value. Hence, the intrinsic value of a call option is either the difference between the security price and the exercise price or zero, whichever is larger. The intrinsic value of a put option is the reverse: the larger of the maximum of $X - S_0$ or zero. For a put, the option is in the money if $X - S_0$ is positive; alternatively, the intrinsic value of the put option is zero.

The percentage change in an option price is typically much larger than the corresponding change in the underlying asset price. This so-called implicit leverage is part of what makes options useful for hedging risk in the underlying asset. But it also means that the value of the option is quite volatile when held by itself, particularly in the case of out-of-the-money options.

3.3.2 Use of options in trading strategies

Options are used in various types of strategies. They are used by both buyers and issuers. Four basic strategies, also called uncovered, naked positions. These are:

- Long Call - The Long Call strategy is one of the simplest option strategies, it is about purchasing the Call option. The investor pays the premium of the option writer, he/she is not obliged to bring and maintain the security deposit. The basic assumption of the Long Call strategy is to play the growth of the underlying instrument (directional strategy). If, at the option execution date, the settlement price is above the option exercise price, the investor will achieve a profit in the amount of the product of points (above the exercise price) and multiplier minus the premium paid. The maximum loss of the Long Call strategy is equal to the premium paid by the option issuer plus a brokerage commission, while the maximum profit is unlimited.

- Short Call - The Short Call strategy consists in the sale of the Call purchase option, it is one of the simplest strategies in which an investor selling options is required to make and maintain a security deposit. An investor using Short Call assumes a decrease in the underlying asset with a drop in volatility, the Call option writer assumes that the predictions of the buyer of the Call option will not work in the future. Issuing the Call option is a strategy that exposes an investor to unlimited losses with limited profits (the maximum profit is the premium received from the option buyer). The option issuer is particularly exposed to risk when selling the OTM option (out-of-the-money), the market movement in the wrong direction forces the investor to keep the security deposit, which increases very quickly.

- Long Put - The Long Put strategy is a directional strategy assuming a decrease in the underlying instrument. As with the Long Call strategy, the buyer pays only for the issuer's bonuses, there is no need to bring and maintain a security deposit. The maximum profit of the Long Put strategy is virtually unlimited (in theory, the value of the underlying instrument cannot be negative) the loss is limited to the amount of the premium paid plus a brokerage commission. An alternative to the above strategy is the sale of a futures contract based on the stock exchange index. The difference is the need to maintain a margin for the contract. For the Long Put option, the investor pays only the issuer's premium.

- Short Put - The Short Put strategy is based on the sale of the Put option, the issuer commits to pay the buyer the option of settlement amount (option buyer's profit) for which he receives a bonus, which is his maximum profit. Shot Put is a typical directional strategy, which assumes that the buyer's prediction options will not work - the option writer is betting on the growth of the underlying instrument. The issue of options is related to the deposit and maintenance of a security deposit, which is charged to the future liability resulting from the option settlement amount (potential gain of the option buyer). Short Put strategy is unlimited risk with limited profits (bonus received), it is particularly dangerous to issue OTM (out-of-the-money) options due to the very rapid increase in the margin in case of unfavorable direction of the investor base instrument (MarketWatch, 2020).

Investors who do not with wish to invest money into traditional futures contracts have can choose to invest by creating synthetic futures contracts. Such contracts can be created by purchases of options on futures, and they can help investors to reduce risk.

There are a number of reasons why options traders use synthetic positions, and these primarily revolve around the flexibility that they offer and the cost saving implications of using them. Although some of the reasons are unique to specific types, there are essentially three main advantages and these advantages are closely linked. First, is the fact that synthetic positions can easily be used to change one position into another when your expectations change without the need to close out the existing ones.

For example, an investor have written calls in the expectation that the underlying asset would drop in price over the coming weeks, but then an unexpected change in market conditions leads to believe that the asset would actually increase in price. If they wanted to benefit from that increase in the same way you were planning to benefit from the fall, then you would need to close your short position, possibly at a loss, and then write puts.

However, they could recreate the short put options position by simply buying a proportionate amount of the underlying assets. They have actually created a synthetic short put as being short on calls and long on the actual stock is effectively the same as being short on puts. The advantage of the synthetic position here is that investor only had to place one order to buy the underlying asset rather than two orders to close your short call position and secondly to open a short put position (optionstrading.org, 2017).

The second advantage, very similar to the first, is that when you already hold a synthetic position, it's then potentially much easier to benefit from a shift in your expectations. An example is a synthetic short put.

Investor would use a traditional short put (i.e. they would write puts) if you were expecting an asset to rise only a small amount in value. The most they stand to gain is the amount you have received for writing the contracts, so it does not matter how much the stock goes up; as long it goes up enough that the contracts they wrote expire worthless.

If they were holding a short put position and expecting a small rise in the underlying asset, but your outlook changed and you now believed that the stock was going to rise quite significantly, they would have to enter a whole new position to maximize any profits from the significant rise.

This would typically involve buying back the puts they wrote (they may not have to do this first, but if the margin required when you wrote them tied up a lot of your capital you might need to) and then either buying calls on the underlying stock or buying the stock itself. However, if they were holding a synthetic short put position in the first place (i.e. you were short on calls and long on the stock), then investor can simply close the short call position and then just hold on to the stock to benefit from the expected significant rise.

The third main advantage is basically as a result of the two advantages already mentioned above. As you will note, the flexibility of synthetic positions usually means that investors have to make less transactions. Transforming an existing position into a synthetic one because expectations have changed typically involves fewer transactions than exiting that existing position and then entering another.

In practice, there is a huge number of complex strategies consisting in combining various options and other derivatives such as futures into one set. Below are presented in basic terms complex strategies using options and futures contracts:

- Long Futures - This strategy involves the purchase of a futures contract, i.e. taking a long position on the futures market with a view that the price of underlying commodity is going to go up and will allow for multiplier effect

- Short Futures - This strategy involves the sale of a futures contract, i.e. a short position on the futures market with a view that the price of underlying commodity is going to go down and will allow for multiplier effect

- Synthetic Long Call = Long Futures + Long Put - This strategy involves the purchase of a futures contract and the purchase of a put option with the same exercise price as the delivery price and the same expiration date as the delivery date. The payout profile from this strategy is the same as the long call strategy. It would typically be used if you owned put options and were expecting the underlying stock to fall in price, but your expectations changed, and you felt the stock would increase in price instead. Rather than selling your put options and then buying call options, you would simply recreate the payoff characteristics by buying the underlying asset and creating the synthetic long call position. This would mean lower transaction costs

- Synthetic Short Call = Short Futures + Short Put - This strategy involves the sale of a futures contract and the sale of a put option with the same exercise price as the delivery price and the same expiry date as the delivery date. The payout profile from this strategy is the same as the short call strategy. Instead of closing your short put options position and then shorting calls, investor could recreate being short on calls by short selling the underlying security. Again, this means lower transaction costs

- Synthetic Long Put = Short Futures + Long Call - This strategy involves the sale of a futures contract and the purchase of a call option with the same exercise price as the delivery price and the same expiration date as the delivery date. The payout profile from this strategy is the same as the Long Put strategy. It is typically used when you were expecting the underlying security to rise, and then your expectations change, and investor anticipates a fall. If you had bought call options on stock that you were expecting to rise, you could simply short sell that stock. The combination of being long on calls and short on stocks is roughly the same as holding puts on the stock – i.e., being long on puts. When investor already own calls, creating a Long Put position would involve selling those calls and buying puts. By holding on to the calls and shorting the stock instead, investors are making fewer transactions and therefore saving costs

- Synthetic Short Put = Long Futures + Short Call - This strategy involves the purchase of a futures contract and the sale of call options with the same exercise price as the delivery price and the same expiration date as the delivery date. The payout profile from this strategy is the same as the Short Put strategy. If an investor was holding a short call position and wanted to switch to a short put position, they would have to close existing position and then write new puts. However, they could create a synthetic short put instead and simply buy the underlying stock. A combination of owning stock and having a short call position on that stock essentially has the same potential for profit and loss as being short on puts

- Synthetic Long Futures = Long Call + Short Put - This strategy involves the purchase of call options and the sale of a put option with the same exercise price as the delivery price and the same expiration date as the delivery date. The payout profile from this strategy is the same as the long-term strategy

- Synthetic Short Futures = Short Call + Long Put - This strategy involves the sale of call options and the purchase of a put option with the same exercise price as the delivery price and the same expiration date as the delivery date. The payout profile of this strategy is the same as the short-term strategy

- Long Straddle = Long Call + Long Put - This strategy involves the purchase of a call option and the purchase of a put option with the same exercise price and the same expiration date

- Short Straddle = Short Call + Short Put - This strategy involves the sale of the call option and the sale of the put option with the same exercise price and the same expiry date

- Long Strangle = Long Call + Long Put - This strategy involves the purchase of a call option and the purchase of a put option with different exercise prices (it does not matter which exercise price is higher) and the same expiry date

- Short Strangle = Short Call + Short Put - This strategy involves selling call options and selling put options with different exercise prices (it does not matter which exercise price is higher) and the same expiration date

- Bull Call Spread = Long Call + Short Call - This strategy involves purchasing call options with a lower execution price and selling call options with a higher execution price and the same expiration date for both options

- Bull Put Spread = Long Put + Short Put - This strategy involves buying a put option with a lower exercise price and selling a put option with a higher execution price and the same expiration date for both options

- Bear Call Spread = Short Call + Long Call - This strategy involves selling call options with a lower execution price and purchasing a call option with a higher execution price and the same expiration date for both options

- Bear Put Spread = Short Put + Long Put - This strategy involves the sale of a put option with a lower exercise price and the purchase of a put option with a higher exercise price and the same expiry date for both options

- Rotated Bull Spread = Short Put + Long Call - This strategy involves the sale of a put option with a lower execution price and the purchase of a call option with a higher execution price and the same expiration date for both options

- Rotated Bear Spread = Long Put + Short Call - This strategy involves buying a put option with a lower execution price and selling call options with a higher execution price and the same expiration date for both options

- Long Butterfly + [Long Call + 2 Short Put + Long Put] - This strategy involves the purchase of a call option (or put option) with the lowest execution price, the sale of two call options (or two put options) with the average exercise price and purchase of the call option (or put option) with the highest exercise price and the same expiry date for all options

- Short Butterfly + [Short Call + 2 Long Put + Short Call] - This strategy involves selling the call option (or put option) with the lowest execution price, purchasing two call options (or two put options) with the average exercise price and call option price (or put option) with the highest exercise price and the same expiry date for all options

- Long Condor = or [Long Put + Short Put + Short Put + Long Put] - This strategy involves the purchase of a call option (or put option) with the lowest execution price, sales the call option (or put option) with a slightly higher exercise price, call option sale (or put option) with an even higher exercise price and purchase of the call option (or put option) with the highest exercise price and the same expiry date for all options

- Short Condor = [Short Call + Long Call + Long Put + Short Put] - This strategy involves selling the call option (or put option) with the lowest execution price, purchase call options (or put options) with a slightly higher exercise price, purchase of a call option (or put option) with an even higher exercise price and call option (or put option) with the highest exercise price and the same expiry date for all options

- Long Strip = Long Call + 2 Long Put - This strategy involves the purchase of a call option and two put options with the same or different exercise prices and the same expiry date for all options

- Short Strip = Short Call + 2 Short Put - This strategy involves the sale of call options and two put options with the same or different exercise prices and the same expiry date for all options

- Long Strap = 2 Long Call + Long Put - This strategy involves the purchase of two call options and a put option with the same or different exercise prices and the same expiry date for all options

- Short Strap = 2 Short Call + Short Put - This strategy involves the sale of two call options and a put option with the same or different exercise prices and the same expiry date for all options

- Call Ratio Spread = Long Call + 2 Short Call - This strategy involves purchasing a call option with a lower execution price and selling two call options with a higher execution price and the same expiration date for all options

- Put Ratio Spread = 2 Short Put + Long Put - This strategy involves the sale of two put options with a lower exercise price and the purchase of the put option with a higher execution price and the same expiry date for all options

- Call Ratio Backspread = Short Call + 2 Long Call - This strategy involves selling call options with a lower execution price and purchasing two call options with a higher execution price and the same expiration date for all options

- Put Ratio Backspread = 2 Long Put + Short Put - This strategy involves buying two put options with a lower exercise price and selling the put option with a higher execution price and the same expiration date for all options

- Conversion = Long Futures + Long Put + Short Call - This strategy involves the purchase of a futures contract at the lowest price, the purchase of a put option and the sale of call options with the same higher exercise price and the same delivery date and expiration date for both options

- Reversal = Long Call + Short Put + Short Futures - This strategy involves the purchase of a call option, the sale of a put option with the same lower exercise price and the sale of a futures contract at a higher price and the same delivery date and expiration date for both options

- Long Box = Long Call + Short Put + Short Call + Long Put - This strategy involves buying a call option, selling a put option both with a lower execution price and selling call options, buying a put option with the same higher exercise price and the same expiration date for all options

- Short Box = Short Call + Long Put + Long Call + Short Put - This strategy involves selling call options, buying a put option both with a lower execution price and buying call options, selling a put option with the same higher exercise price and the same date expiration for all options

- Neutral Calendar Spread = Short Call + Long Call - This strategy involves the sale of a call option with a specified exercise price and the purchase of a call option with the same exercise price, but a longer expiration date. We select options whose exercise price is close to the current share price

- Bullish Calendar Spread = Short Call + Long Call - This strategy involves selling a call option with a specified exercise price and purchasing a call option with the same exercise price but a longer expiration date. We select options whose exercise price is higher than the current share price

- Bearish Calendar Spread = Short Call + Long Call - This strategy involves the sale of a call option with a specified exercise price and the purchase of a call option with the same exercise price but a longer expiration date. We select options whose exercise price is lower than the current share price

- Diagonal Spread - This strategy involves the use of purchase and sale options that differ in both the exercise price and the expiration date (Shap, 2005, p. 40).

Calendar Spread

It is also important to define the Calendar Spread method in detail typically used on the Futures markets. It is also known as intracontract, intracommodity, intermonth or time spread.

Spread strategies on the futures market consist of simultaneous purchase and sale of futures contracts for the same underlying instrument, but with different delivery dates or simultaneous purchase and sale of contracts for various underlying instruments and with the same or different delivery dates (inter-brand spread, also referred to as as an intercontract or intercommodity spread) (Shap, 2005, p. 41).

Positions occupied in the spread are called spread legs. In the calendar spread, they are referred to as correlated positions, as they refer to contracts of the same class, although other series. An increase in the price of the underlying instrument should result in an increase in the price of the derivative, with the effect being stronger for the series with a closer expiry date. This is related to the convergence of spot and futures prices as the expiry date approaches. In an effective market, the convergence of prices is the greater, the closer to the end of the contract.

Prices of base and derivative instruments are more strongly correlated, closer the contract expiration, and a contract with a closer date is more strongly correlated with the underlying instrument than a contract with a further term (deferred, distant). When the price of the underlying instrument increases, the price of the shorter contract should grow faster than the longer one (Shap, 2005, p. 59). However, when the price of the underlying instrument decreases, the price of the shorter contract should fall faster than the longer one. At the same time, the biggest differences should occur between extreme contracts, i.e. the shortest and the longest ones.

Taking opposed positions within the calendar spread means gaining profit on one position and a loss on the other. Gains and losses do not compensate completely because of the different reactions of each series. It is important how the difference will be shaped, i.e. the spread between the quotation of a contract with a closer and longer expiration date. The difference may increase (spreads) or decreases (weakens) (Gannon, 2010, p. 187).

The increase in the price of the underlying should be accompanied by the strengthening of the spread (less negative or more positive spread), and decrease - weakening of the spread (spread less positive or more negative)

When investors expect prices to increase in the cash market, they apply the bull intracontract spread strategy, i.e. buy a shorter contract and sell it for a longer period. Such a strategy is called the purchase of a spread. If, on the other hand, they expect the prices of base instruments for contracts to fall, they implement the bear intracontract spread strategy - sell a contract with a closer expiration date and simultaneously buy a contract with a further term. This is called sale of the spread (Shap, 2005, p. 145).

At the same time, it does not matter if the rates will go up or down. All that needs to be done is to predict whether the price difference will increase or decrease. An investor buys a spread when it expects its strengthening but sells it when it expects it to weaken. If the investor's expectations regarding the change in spread are successful, then he or she will make a profit, if not – the investor will incur a loss.

The choice of an option strategy depends on at least two investor perspectives— on the direction (up or down) of the price change for the underlying security and on the cost (cheap or expensive) of the options (Clarke, et al., 2013).

3.3.3 General investment strategies:

Investing is associated with refraining from current consumption for future, albeit uncertain benefits. The goal of investing is to achieve the highest possible rate of return at an acceptable level of risk (Investopedia, 2021). The way of investing capital on the stock market depends on many factors, dependent and independent of the investor, such as:

- expected rate of return
- tendency to accept the risk
- investment horizon
- level of knowledge about investing and experience in the capital market
- personal situation - age, family status, health status
- economic situation - owned property, savings, free funds, personal income, debt
- share of investment in personal assets
- available time to dedicate to analysis and monitoring of the stock market situation
- the level of capital market development and access to it
- situation on the capital and macroeconomic market

1. Speculation.

Speculation is the most popular investment technique. The investor buys financial instruments to sell them later, hoping to increase their prices. Speculation can also be calculated on the fall in quotations of financial instruments. In the forward market, it may be the sale of forward contracts or short sales in the case of securities. Speculative risk depends on the type of financial instruments, price volatility, liquidity and market type. To obtain income from speculation, it is crucial to choose the right time to acquire securities and then resell them. A characteristic feature of speculative financial instruments are large fluctuations in quotations that may lead to their unreasonable re-evaluation, ie the creation of a speculative bubble. The effect of speculation may also be the undervaluation of financial instruments, including related assets, such as commodity prices, through a speculative game for a discount on futures contracts. Speculators with low liquidity and strategic asset markets are particularly sensitive to speculative activities.

2. Short sale.

Short sale is a strategy of investing on the stock exchange consisting in the sale of borrowed securities and then their purchase and return to the lender. At the time the short sale transaction is concluded, the investor does not have any securities on the securities account, but is obliged to deliver them on the transaction settlement day. For this purpose, it lends securities to a financial institution, such as a brokerage house, which holds them on its own account, bank, investment fund or other investor. A securities loan in this case means a temporary transfer of ownership of the securities to the borrower. In order to close the short position, the investor buys the same number of securities on the market and returns to the lender. The investor pays a fee for the loan received in accordance with the contract concluded with the lender. The existence of a liability in securities means a short position. The financial result of this operation is the difference between the selling price and the purchase price. Thus, short sales allow you to make profits on declines in securities quotes. However, if securities prices rise, the short position generates losses. The strategy of short selling is riskier than speculation, because the potential loss is theoretically unlimited.

3. Buy and Hold strategy.

An investor using the "buy and hold" strategy selects shares on the market that, according to his predictions, have a chance to grow in the medium or long term. The composition of the portfolio thus created does not change over the assumed investment period. This strategy brought Warren Buffett a huge fortune.

4. Market timing strategy.

This strategy involves predicting the directions of changes throughout the capital market and quick response by purchasing selected financial instruments and reselling them at a profit. The composition of the investment portfolio with this strategy undergoes frequent changes.

5. Opportunistic strategy.

The investor seeks to take advantage of the opportunity to conclude a favorable transaction. This requires constant monitoring of the market because the best investment opportunities occur sporadically and usually last for a short time. This strategy can therefore bring profits in every market situation.

6. Behavioral strategy.

The investor makes investment decisions guided by the analysis of the capital market psychology. This is the field of knowledge referred to as behavioral finance. It allows one to understand the rules of crowd behavior and predict the behavior of stock investors in various market scenarios.

7. Benjamin Graham's strategy.

The investor focuses on determining the company's internal value. Striving to buy its shares below internal value wants to guarantee a safety margin. Graham distinguishes three ways of investing, which can be described as:

- investing in current assets
- defensive investing in value
- entrepreneurial investing in value

8. Strategy for averaging the purchase price.

The investor buys a certain number of shares of the selected company at set intervals. As a result, the purchase price of a block of shares is equal to the product of the total number of shares and the average price of the purchased shares after which the shares were bought. In this strategy, it is impossible to invest all capital at the least favorable price.

9. Strategy of a fixed capital structure.

The investor divides the capital into two parts in a certain proportion, preferably in half. One part of the capital is intended for the purchase of shares, and the other part for the purchase of safe financial instruments, e.g. treasury bonds. Depending on the market situation, the investor rebuilds the portfolio so that the value of owned shares remains unchanged.

10. Strategy to maintain a constant ratio.

The investor divides the capital into two parts in a specified proportion. One part is for the purchase of shares and the other part for the purchase of safe financial instruments. Depending on the situation on the market, the investor purchases or sells one or the other, striving to keep the ratio determined at the beginning.

11. Price-indicator strategy.

The investor decides to buy or sell shares based on the price / earnings ratio (P / E) or price / book value ratio (P / BV) previously determined. In the event that the ratio for the given shares reaches the upper value, the investor sells them. If it falls to the lower value of the range, then the investor buys additional shares. No transactions are made at the P / E or P / BV ratio within the set interval.

12. The strategy of preserving capital.

The investor buys liquid financial instruments, usually yielding a low but sure income, and allows for the recovery of the invested capital at any time. Such an investment is characterized by low risk but also low earning potential. Proper for investors who have risk aversion, not expecting rates of return far outperforming inflation, but received systematically.

13. Current income strategy.

The investor buys only such assets, which primarily generate a constant stream of income from the invested capital. Investments include financial instruments with fixed and certain income, e.g. interest on bonds. This strategy is used by investors who want to increase their current income and do not intend to bear excessive risk (LeBaron, 2002, p. 50).

General investment styles:

Regardless of the strategy, investors apply their own investment styles. The choice of style depends mainly on the expected rate of return and the level of acceptable risk.

1. Conservative investment style - involves investing capital in the most secure financial instruments: treasury bills, safe bonds, investment certificates of guaranteed investment funds, structured products with guaranteed return of capital. This investment style is appropriate for people who do not expect high returns with a high-risk aversion.

2. Sustainable investment style - it involves investing capital in shares and safe financial instruments, e.g. bonds of solid issuers. Risk level and rate of return - medium, depending on the proportion between risky assets and safe assets.

3. Aggressive style of investing - it involves investing capital in financial instruments that are distinguished by high price volatility, such as shares of dynamic companies, structured products without a guarantee of capital, or derivative instruments. This style is used by investors expecting high rates of return, accepting high risk (Jorgenson, 1963).

In conclusion, the catalog of strategies and investment styles can be arbitrarily wide. Each investor can create their own rules for building a portfolio. However, regardless of the strategy or style chosen, consistency should be maintained. Only when certain rules are observed can you count on the achievement of the intended investment objective.

Many types of information related directly and indirectly to the capital market create a specific picture of it and possible tendencies, but there is also a need to feel the market that has a significant impact on the effectiveness of the investment decision. It is expressed in a good synchronization of the exchange and over-the-counter operations with market changes and ensures the achievement of success. The feeling of moments of changes in the market situation is of particular importance, especially during bull market or bear market and a quick and determined adaptation of investment decisions.

An important area of action is the verified collation of a portfolio of securities. Their main groups are short-term debt securities market and bonds and stocks, constituting the capital market's underlying instruments. Effective investment strategies should be characterized by the ability to adapt to the changing market situation. Therefore, the structure of the investment portfolio depends on the relationship between the profitability of investments in given securities and risks and should be shaped accordingly flexibly (Bernsten, 2010, p. 188). By valuing income from various groups of long-term and short-term securities, the mechanisms of the modern capital market allow for effective transfer of capital from one to the other. Depending on the profitability of the investment, which may be conditioned by changes in interest rates, overvaluation or undervaluation of given securities (e.g. shares) or other reasons.

Fundamental investment principles also include the need to have a long-term concept, resulting from the investor's preferences, its predisposition, risk propensity and other factors that can be included in the investment philosophy.

4. DEVELOPMENT OF A MODEL TO PREDICT NEW UPWARD TRENDS IN GOLD FUTURES PRICES USING MACHINE LEARNING ALGORITHMS.

4.1 Introduction

4.1.1 Problem Statement

Futures contracts are a type of forward contract between a buyer and a seller of an asset. They stipulate exchange of goods and money at a future date at a price and quantity determined today. Gold futures are one of the most traded contracts, which at the time of writing, allows a person to own rights to 100 troy ounces of gold for ~ $8,000. With gold currently trading around $1,400 mark, 3% change in contract price allows for ~ $4,000 profit or loss. The contract is marked to market and profits and/or losses are posted to margin account on a daily basis.

Common strategy for entering to long positions is by studying relationships between moving averages of different lengths prior the development of new trends. Generally speaking, formation of every new upward trend has a number is preceded by some shorter moving average crossing a longer moving average upwards. After studying gold futures prices since 1974 the following selections were made

- 4-day and 9-day moving averages (MA) of daily close for signals
- 9-day Average True Range (ATR) as a measure of implied volatility
- Daily close price on 6th day after signal as target dependent variable

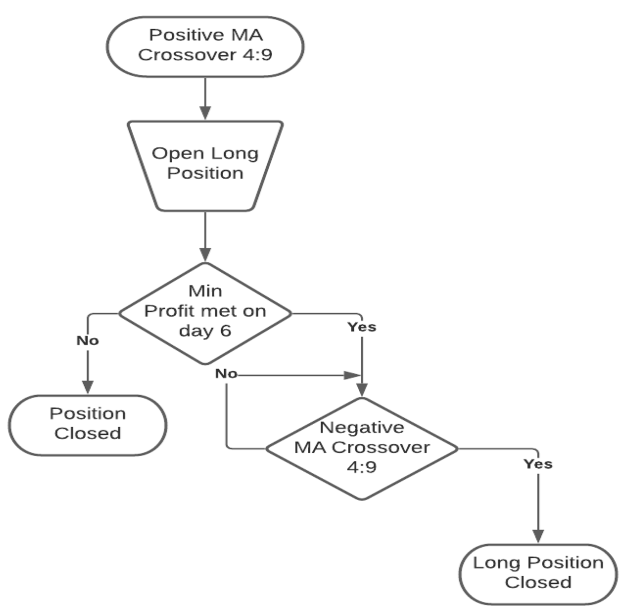
The above were derived by performing back-testing of various options due to the following:

- 4-day MA crossed 9-day MA on the way up over 660 times between 1974 and 2018, providing a reasonable number of observations for statistical analysis
- Daily close price has the smallest variance out of Open, Close, Min and Max prices and position can be entered in at very similar price after market reopens for after-hours trading
- 9-day ATR was derived via back testing of different lengths of ATR starting from generally recommended 14 days and reducing the number until trades became profitable on 30% of occasions

- 6-day after signal window were derived by back testing different numbers to make sure that at least 90% of new longer trends (4-day MA staying above 9-day MA for at least 9 days) are captured. In other wards if close price on day 6 was not higher that close price on signal date plus 9-day ATR then there is less that 10% chance of new positive trend happening

Based on the above initial strategy before performing any modeling is to enter into long positions on gold futures at the market price following the crossover with a view of holding the contract for six or more days if upward trend develops. The minimum profit target is 9-day ATR, which also becomes maximum acceptable loss on any trade. Positions are closed in cases when minimum profit target is not met on day six. In case if minimum profit target is achieved, position is kept open until a new 4-day and 9-day MA crossover with 4-day MA going down. Below is the initial decision tree for trading.

Figure 4.1: Decision Tree for Trading



Back testing shows that this approach is moderately profitable as in ~30% of instances new upward trend materializes with average profit significantly higher than the average loss, however it is difficult to define exact Return on Investment (ROI) due to the fact that cost of capital varies significantly between 1974 and 2018 and trades and results were not spread evenly.

The author would like to improve upon this approach and develop a probabilistic model that can be used as a guide to risk of proposed trades at the time of entering positions. The model should include available historic price, volume and open interest trend data which can be derived from available variables. They are momentums of the variables for various lengths of time, ratios of current price to maximums and minimums of time periods and other technical indicators used by traders. The author would like to explore the predictive power of these derivative variables and develop methodologies that will incorporate the data in the decision management process.

4.1.2 Research Purpose

The purpose of this research is to determine whether derivative variables can better predict a new upward trend in Gold Futures and improve the profitability of these investments. The findings from this research will help traders understand the predictive power of derivative variables and help with decisions about entering trades and allocating capital. Gold futures were selected for this research due to the following:

- Only Gold futures had verifiable daily data starting from 1974
- Gold futures history was adequate to expect enough observations to have statistically significant results when using daily data
- Gold futures were the most traded metals futures in the United Sates in every year when comparison was available (statista, 2020)
- There was no record of high concentration of Gold futures in any period as opposed to most of the agricultural futures

The model features will be engineered from available Gold Futures data. This research will explore the relationship between historic prices and future prices on dates with preset criteria.

Brokerage fees were omitted from consideration due to the following:

- When data was first extracted in December 2018, Gold futures traded above $1,200 per ounce

- Minimum expected profit from single trade which equals maximum allowable loss during 2017-2018 was based on over 200 ticks which equals to over $2,000
- Brokerage fees per contract at the same time were $2.50 which equates to approximately 0.1% of expected profit or loss.

4.1.3 Variables and Scope

For this study, the author only considered those dates when 4-day MA crossed 9-day MA upwards. Prices from 6 days after crossover are used to classify which trades achieved minimum profitability target. If price is above target, then dependent variable equals 1, else it equals 0.

Available daily price data since 1975 was extracted from Barchart.com using API:

- Open Price
- High Price
- Low Price
- Close Price
- Volume
- Open Interest

Data features were engineered for independent variables by calculating various types of momentums available variables and ratios of last known prices to minimums and maximums of different lengths of time. Below are groups of the feature-engineered, independent variables[1]:

- Momentum for all available variables using 1,4,9,15,30 and 60 days and its moving average using 4,9,15,30 and 60 days
- Momentum for close price weighted by Open Interest, Volume and both. Its moving average using 4,9,15,30 and 60 days

[1] Full list of variables extracted from bank statements is included in Appendix A.

- Ratio of Close price to Minimums and Maximums of Close price in the last 4,9,15,30, 60,90,180 and 360 days
- Ratio of Close price to Bollinger Bands and its moving averages for 4,9,15,30, 60 and 90 days
- Daily difference between price of Futures contract and physical gold and its moving averages for 4,9,15,30, 60 and 90 days

4.1.4 Research Question and Hypotheses

This research aims to answer the question "Can traders utilize the data created from historic prices to improve profitability of bets on upcoming upward trend?" The analysis builds machine-learning models that can be applied to future trades. It tests the predictive power of these models and created variables. Models can be tested on other Futures contracts and adjusted accordingly in order to diversify trading and increase volume of trades. The hypothesis is that created data can help to identify 90% of successful trades with accuracy over 50%.

4.1.5 Literature Review

Gold Futures is old financial instrument with limited published quantitative research. Building statistical models to predict price of a commodity and use it in trading is typically limited to trading houses that keep most of their research in-house as means of competitive advantage. Peer reviewed literature in this area is scarce as well.

A book on derivatives trading, *Money Management Strategies for Futures Trades* by Balsara (Balsara, 1992), states "A buy signal is generated when the shorter of two moving averages exceeds the longer one; a sell signal is generated when the shorter moving average falls below the longer moving average." It follows with "Armed with this information, the trader can estimate a cutoff value, beyond which it is highly unlikely that the unrealized loss will be recouped, and the trade will end profitably."

Some researchers (Luo, et al., 2019) experimented with predicting prices of oil futures using Convolutional Neural Network (CNN). Their research concluded CNN produces better results than traditional economic models, but not accurate enough to be useful. That is due to complex nonlinear characteristics of the relationships coming from "many complex natural, economic, and political factors". No similar research related to Gold Futures was found.

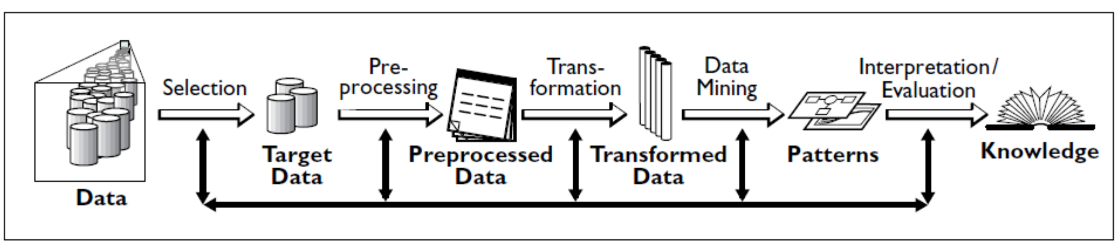
All non-academic sources for traders suggest using maximum allowable loss from the trade when betting on a new trend. There is however no concept of "minimum target profit" or minimum duration of time that the contracts are targeted to be held. The author suggests that establishing these new metrics and calculating statistical probability of profit happening can enhance trading strategy by foregoing some of the trades when signals happen. or allocating smaller amount of capital to them or exploring low risk strategies such as calendar spreads.

4.2 Methodology

4.2.1 Analysis Framework

This research follows the Knowledge Discovery and Data Mining (KDD) structure, illustrated below.

Figure 4.2 KDD Framework



The framework comprises finding the data source, pre-processing and transforming the data, followed by descriptive analysis and modeling, and finally interpreting the outcomes. The best outcomes lead to knowledge which can be acted upon. All steps are described in the following sections.

4.2.2 Data Description

Barchart Inc. has been identified as potential data source. Their free API service was used for downloading of the initial data set. It contained over 11,000 daily observations of Gold Futures prices as well as Open Interest and Volume of trading by day. Each day had 4 price points: open, low, high and close. The data was downloaded in structured spreadsheets format using R interface. Spot prices for Gold were downloaded separately from the same source and merged to initial dataset.

4.2.3 Development of Dependent Variable

The application of supervised machine learning algorithms requires for each observation to have a dependent variable as outcome measure and independent variables as predictors. Daily price data was used to create both dependent and independent variables.

Daily Close price was selected as basis for analysis due to the fact that it is the price that can be used to enter positions after performing statistical analysis on daily basis. US markets stop trading at 5pm Eastern time and vast majority of day traders are no longer active, therefore removing intraday volatility. All open interest afterwards is from medium and long-time investors who can afford both intraday and overnight margin requirements.

There is a 60-minute break in trading on COMEX. When electronic trading resumes at 6pm Eastern time, bid and ask prices are typically within few ticks from the Close price. That allows for one hour to run models and make decisions on opening new positions.

Moving averages of Close price have been calculated using 9-and 4-day periods, followed by calculation of difference between them using shorter average as basis. All observations when the difference turned positive from being negative the day before were identified and Signal date. These lengths of MA were selected after performing a data exploration exercise of daily Gold futures prices between 1974 and 2018. Using 4 and 9-days allowed to have 639 Buy Signals when first MA crossed the latter on its way upward.

ATR was selected as a measure of volatility with a length of 9 days, including Signal date. This calculated measure also became a minimum profit and maximum loss targets for the trades and was added to Close price on each signal date. Target price was calculated by adding Minimum profit target to Close price on Signal date. This calculated Target price was then compared with actual Close price on day 6 from Signal date. If actual price was above target price, then the trade was regarded as profitable and dependent variable was coded as “1”. If the condition was not satisfied, then dependent variable was coded as “0”. 9-day ATR was selected a optimal together with 6-day waiting period as they maximized the number of profitable trades over the available time horizon with approximately 2 in 3 signals becoming false positives. The remaining trades would become profitable with average profit of 3x minimum profit target when using da

4.2.4 Development of Independent Variables

It is popular between traders and analysts to use Momentum, to define trends in prices and make decisions. With that in mind it was calculated for all available variables utilizing commonly used periods of 1, 4, 9, 15, 30, 90, 180 and 300 days. These new variables were used to create to create moving averages of them. For price variables weighted moving averages were also calculated using Volume and Open Interest as weights.

Additional features related to potential levels of price resistance and market sentiment were created:

- Ratios of Close price to Minimums and Maximum prices of periods of different lengths: 9, 30, 60, 90 and 180 days
- Daily difference between Future Close price and Spot price of gold and its moving averages for 4, 9, 15, 30, 60 and 90 days

A total of 163 independent variables (Appendix i) were created and attached to dependent variable. Due to some missing data and the fact that some of the independent variables could not be calculated for the first year of available data, 634 out of available 650 observations were selected for analysis. They were split into Training and Testing datasets using 70/30 ratio.

4.3 Modeling

4.3.1 Descriptive Analysis

The Weight of Evidence (WOE) and Information Value (IV) framework was used for exploratory analysis and variable screening for binary classifier, being dependent variable. According to Larsen (Larsen, 2016) WOE and IV enable to:

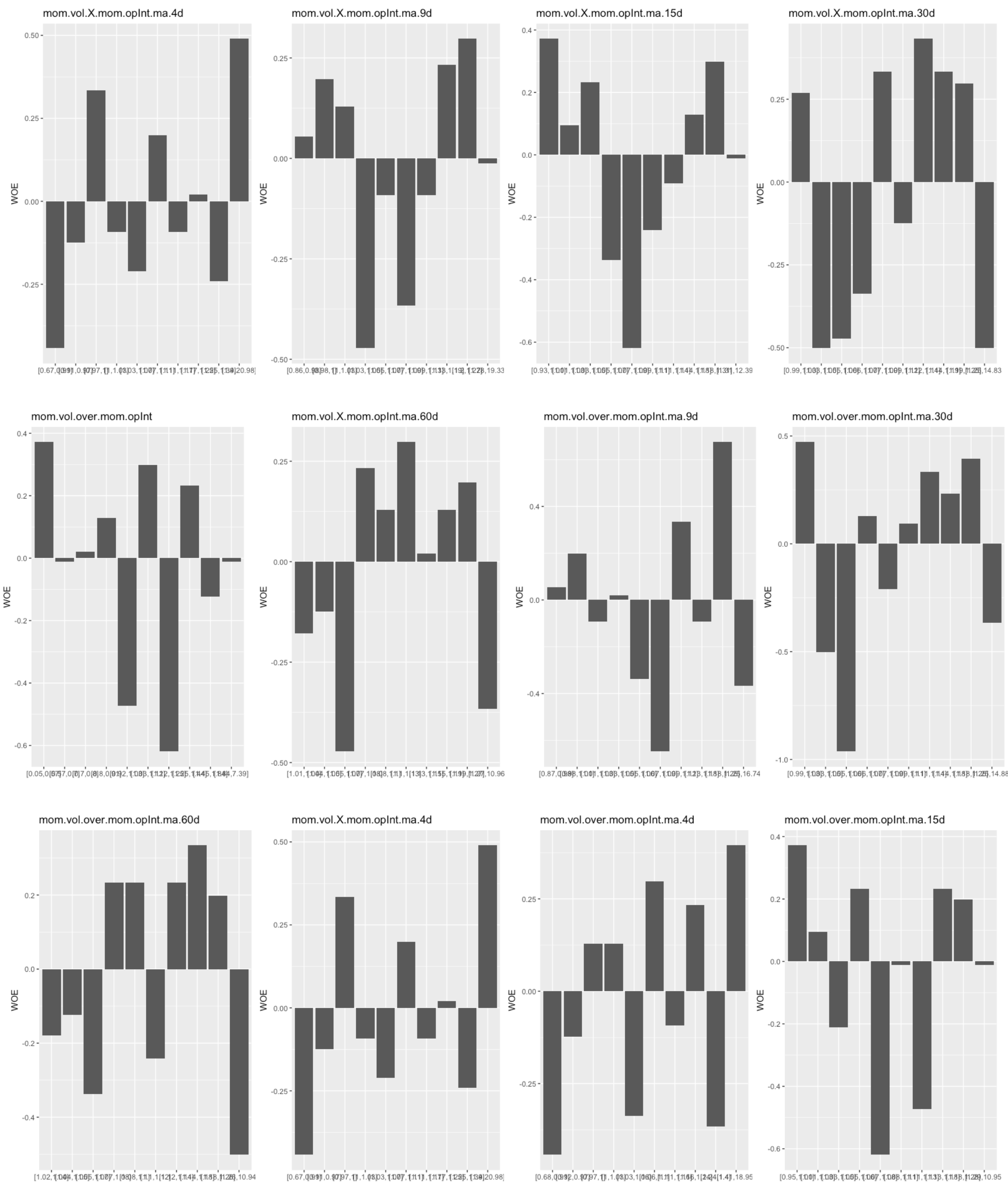
- Consider each variable's independent contribution to the outcome.
- Detect linear and non-linear relationships.
- Rank variables in terms of "univariate" predictive strength.
- Visualize the correlations between the predictive variables and the binary outcome.

WOE and IV play two distinct roles when analyzing data:

- WOE describes the relationship between a predictor and a binary target variable.
- IV measures the strength of that relationship.

Using Testing dataset WOE and IV were calculated. Below table depicts top 12 variables by IV. Their distribution suggests a non-linear relationship between dependent and independent variables.

Figure 4.3: Information Value and Weight of Evidence



In order to understand if the same patterns show in Testing dataset, the Net Weight of Evidence (NWOE) and Net Information Value (NIV) were calculated by deafferenting WOE and IV of Training and Testing datasets. The table below shows top 10 variables by NIV. It appears that the penalty introduced by the differences between datasets is very high comparing to original values calculated from Testing dataset and NIV is less than half of what was initially expected. That further complicated research as it implies that findings from Testing are not likely to be validated and suggest that better results may be achieved from unsupervised models such as Neural Networks.

Table 4.1 Top 10 variables by Adjusted Information Value

	Cluster	Variable	IV	PENALTY	AdjIV
62	45	mom.49d.ma30cl	0.21430317	0.12541399	0.0888891803
52	35	mom.90.180.ma30cl	0.24042815	0.15998139	0.0804467672
76	59	cl.max15	0.27075677	0.22341167	0.0473450940
72	55	cl.max60	0.09868773	0.05796630	0.0407214349
29	19	mom15c9ma	0.17362132	0.13898644	0.0346348816
74	57	cl.max30	0.13911815	0.10484595	0.0342722027
69	52	cl.min180	0.12282260	0.08897672	0.0338458741
131	91	ma.fut.spot9d	0.17035145	0.13852668	0.0318247693
130	90	ma.fut.spot15d	0.24107789	0.21012616	0.0309517249
139	94	mom1c	0.06906315	0.03937413	0.0296890180

4.3.2 Variables Selection

Independent variables were created with high degrees of correlation as the same original variables were used in different manners with expectation that some of them may have marginally better predictive power then others. A high degree of correlation causes issues with most supervised MALs so dimensionality reduction needed to be performed.

In order to achieve that and select most usable predictors, Variable Clustering was performed, using previously calculated IV. It divided variables into mutually exclusive clusters such that:

- the correlations between variables assigned to the same cluster are maximized.
- the correlations between variables in different clusters are minimized.

Using different cutoff levels for variables correlation 2 datasets were created:

- 24 variable dataset with no correlation above 0.8, most suitable for MLAs sensitive to multicollinearity such as regressions and trees

- 123 variable dataset with no correlation above 0.92, most suitable for MLAs not sensitive to multicollinearity such as Neural Networks (NN).

4.3.3 Logistic Regression

Binary Logistic Regression is a type of regression in which the binary response variable is related to a set of discrete or continuous explanatory variables. It was tested with 24 explanatory variables for completeness purposes despite exploratory analysis findings of lack of linear relationship. The best model had 3 significant variables and it failed to predict more than 2% as "1"s in both Training and Testing.

The use of Logistic was extended to with using Principal Components (PC) of 123 variables and Regularized regression that penalizes coefficients that do not add value. Only one out of 18 PCs that explained 80% of the variance was selected as significant. All coefficients were suppressed to "0" in Regularized regression. Neither predicted over 3% as "1" in Testing or Training.

4.3.4 Decision Tree

CART Decision Tree is a type classification methodology, in which the tree is obtained by recursively partitioning the data and fitting a prediction model within each partition. In order to avoid overfitting, the minimum split was set to 20 in this study; the tree will only split when there are at least 20 observations in each branch. The result was promising in Training stage with 29% observations predicted as "1" with 74% accuracy. It did not hold for Test dataset with accuracy of prediction of "1" dropping to 30% in line with random choice. This kind of result was expected based on differences between WOE and IV between Training and Testing datasets.

4.3.5 Random Forest

Random Forest is an ensemble method that constructs multiple decision trees and outputs the single tree, which is the mode of the individual trees. The number of trees built was set to 200 given the relatively small data set. Different max depth values from 2 to 15 were tried and based on the best 5-fold cross-validation, the tree with a depth setting of 5 resulted in an 29% predicted as “1” with 87% accuracy. Similarly to CART this result reverted 28% accuracy with 30% observations predicted as “1”.

4.3.6 Gradient Boosting Classifier

Gradient Boosting (GB) is an ensemble method that produces a prediction model in the form of weak prediction models, typically decision trees. The model descends various stages until it finds an optimal value for the coefficients. Like Random Forest. the number of trees was set to 200 with various depth settings. Unlike Random Forest, a learning rate was required for the boosting process. Various settings for the depth and learning rate were tried, however none of them managed to predict any “1” in Training. The Gradient Boosting Classifier was therefore discarded as option.

4.3.7 Neural Networks

MLPs with a number of layers between one and six were tested with various activation functions for layers. Best results for dataset with 123 variables were produced by a model with 3 hidden layers and Rectifier Linear Unit (ReLU) activation function. Table 4.2. It produced accuracy of over 50% in identification of “1” in both Training and Testing. Overall percentage of predicted “1”s was low in both instances ranging between 11% and 14%. Lowering probability cutoff did not help as increase of predicted “1” was accompanied with drop of accuracy to Random Choice level.

Table 4.2: Confusion Matrix of NN model with 123 Variables

Event (Random Choice)	Holdout		Training	
	Predicted 0 (Accuracy %)	Predicted 1 (Accuracy %)	Predicted 0 (Accuracy %)	Predicted 1 (Accuracy %)
0 (70%)	132 (76%)	11	280 (73%)	24
1 (30%)	41	17 (61%)	104	25 (51%)
Predicted % of Total	84%	14%	89%	11%

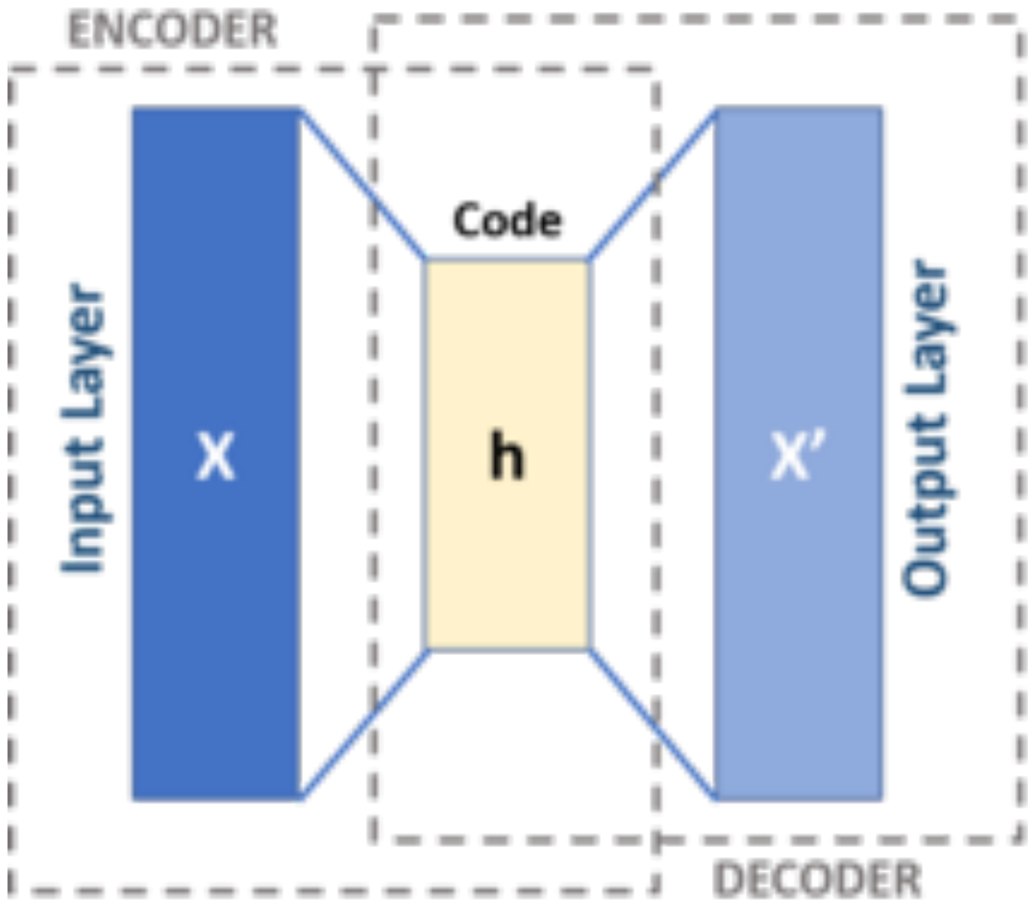
Independent variables sensitivity analysis was performed and allowed to select 24 variables responsible for the most variation of dependent variable. A model with the same parameters was trained using dataset with 24 variables. It gained results slightly worse in terms of accuracy of predicting “1;” however it predicted significantly more of them in both Training and Testing. Accuracy was 55% for Training and 43% for Testing with proportion of predicted “1” being 19% and 21%.

Table 4.3: Confusion Matrix of NN model with 24 Variables

Event (Random Choice)	Holdout		Training	
	Predicted 0 (Accuracy %)	Predicted 1 (Accuracy %)	Predicted 0 (Accuracy %)	Predicted 1 (Accuracy %)
0 (70%)	115 (74%)	24	267 (76%)	37
1 (30%)	41	18 (43%)	83	45 (55%)
Predicted % of Total	79%	21%	81%	19%

Seeking further improvements, other types of NNs were tested with one Deep Learning (DL) model producing interesting results. The process, called autoencoder, depicted in graph 3.4.6.X. often used for anomaly detection. It is a symmetric feedforward Neural Network with the purpose of reconstructing its inputs instead of predicting the target values. For this research it involved creating a model with Training dataset consisting only with observations where dependent variable was “0”. It was then trained with inputs equaling outputs in order to learn what the “normal” process looks like. After that “1”s from Training and Testing datasets were introduced to the model and their error terms were measured.

Figure 4.4: Generic Autoencoder Diagram



Below is reconstruction error by class for Autoencoder with 4 dense layers and 24 variables

Figure 4.5: Reconstruction Error of Autoencoder with 24 Variables

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The best result from this model is achieved using Reconstruction Error cutoff of 0.02. Almost 20% of observations lay below the cutoff line with proportion of “1” of only 8%. It still has 35% accuracy in identifying “1” in the remaining population, but the accuracy of identifying “0” below the line is the best seen in this analysis.

Assessing model performances:

Among all classification methods, only Neural Network models produced results with accuracy of identifying "1" of greater than 40%, when predicting 20% observations as "1" and accuracy in identifying "0" of over 90% for 20% of the observations. Model with 123 variables achieved 50%+ accuracy in both Training and Testing but the proportion of predicted "1" was 11% and 14%. Due to Neural Networks being "black-box" methods, understanding of the importance of individual variables cannot be achieved.

4.3.8 Validation of assumptions

No assumptions were made about the form of either the true functional dependence or the form function estimate. These models did not need a linear relationship between the dependent and independent variables. In fact, these models supported many types of relationships. Also, the variances did not need to be heteroscedastic for each level of the independent variables. Instead, the analysis focused only on the predictive ability of the models.

4.3.9 Model validation

Traditional Verification and Validation (V&V) techniques such as cross-validation cannot be applied to Neural Networks due to their "black box" structure (Tim Menzies 2005). The only validation of the model developed using Training dataset was to apply holdout Testing dataset for binary classification models. Validation of time-series models was performed on a rolling window basis with a model moving one signal at a time before every re-fit.

4.3.10 Time-series approaches

Time-series approach, using structural time series model is defined by two equations. The observation equation relates the observed data $\boldsymbol{y_t}$ to a vector of latent variables $\boldsymbol{\alpha_t}$ known as the *state*

$$\boldsymbol{y_t} = \boldsymbol{Z_t^T \alpha_t} + \boldsymbol{E_t}$$

The transition equation describes how the latent state evolves through time

$$\boldsymbol{\alpha_{t+1}} = \boldsymbol{T_t \alpha_t} + \boldsymbol{R_t \eta_t}$$

The error terms $\boldsymbol{E_t}$ and $\boldsymbol{\eta_t}$ are Gaussian and independent of everything else. The arrays $\boldsymbol{Z_t}$, $\boldsymbol{T_t}$ and $\boldsymbol{R_t}$ are structural parameters. This approach was described in detail in chapter 2.4.5 and has been considered due to availability of well-developed set of MCMC algorithms for doing Bayesian inference with time-varying .

The logic to define prediction in confusion matrix is as follows:

- If prediction is above target price and actual comes above target price than it is a True Positive
- If prediction is above target price and actual comes below target price than it is a False Positive
- If prediction is below target and actual comes below target price than it is a True Negative
- If prediction is below target price and actual comes above target price than it is a False Positive

The model was first trained with all data starting in 1975 through first Signal in 2005. Then it was re-fit for every signal until the end of 2014 and Forward Validation was performed using data from 2015-2019. Each Trend and Regression component was used separately, then they were ranked by predictive power. For final model best Trend component was selected first, then Trend components were added until model stopped improving. Then Regression components were added the same way.

Final model includes two trend components (Local Trend of Close Price and Local Trend of High Price) and two regression components (3-day lag of Close Price and 3-day Lag of High Price). Accuracy of predictions for Training and Validation periods are significantly higher than for any model previously considered. Table 4.4. Direct comparison is not possible, however, due to differences in approaches and how dependent variable is used for modeling.

Table 4.4: Confusion Matrix of BSTS model with 4 components

Event (Random Choice)	Holdout		Training	
	Predicted 0 (Accuracy%)	Predicted 1 (Accuracy %)	Predicted 0 (Accuracy%)	Predicted 1 (Accuracy%)
0 (70%)	33 (86%)	4	99 (92%)	10
1 (30%)	5	16 (75%)	9	30 (75%)
Predicted % of Total	66%	34%	73%	27%

Attempts were made to reproduce results from BSTS by applying Deep Convolutional and LSTM Recurrent Neural Networks algorithms to gold futures data. Same logic was followed, trying to predict Close price on day six after signal, but results obtained were not similar to those from BSTS in terms of accuracy. Attempts to use feature engineering and experimentation with layers did not show any improvements.

4.4 Summary and Conclusion

4.4.1 Descriptive Analysis Results

As we explained in our descriptive analysis section, the relationship between dependent and independent variables is weak and non-linear. That prevented us from understanding of importance of specific predictive variables.

4.4.2 Modeling Results

Predictive power of historic data:

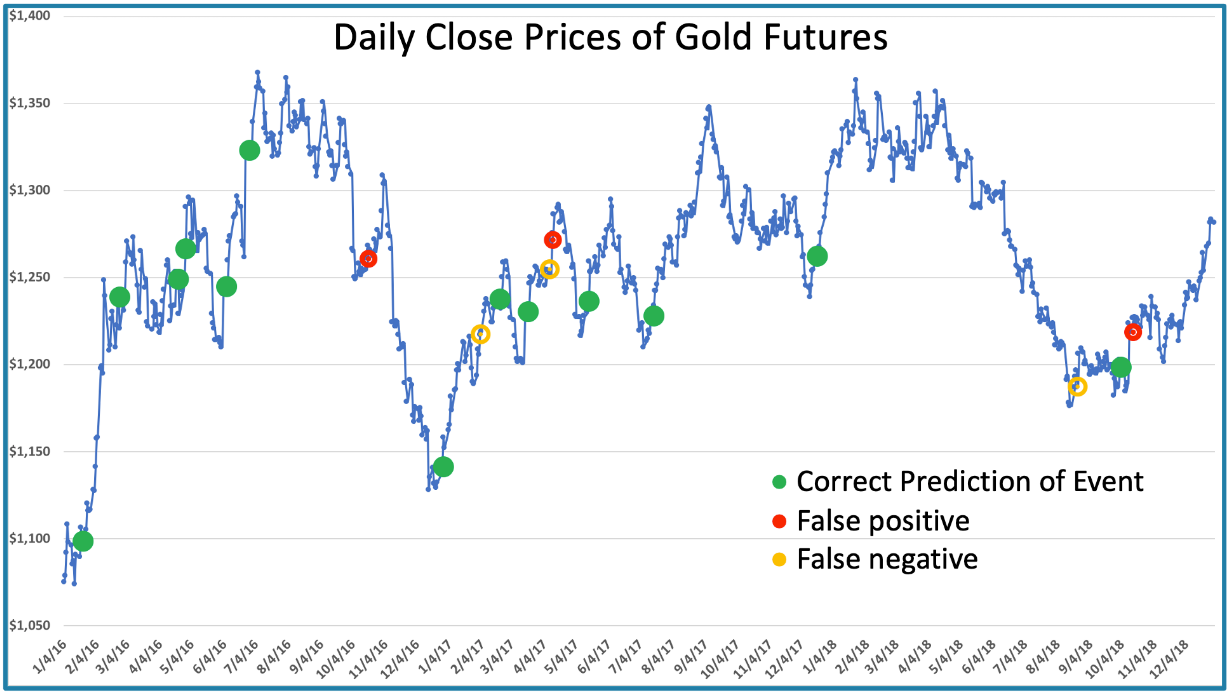
Through the construction of multiple predictive models using various machine learning techniques, historic price data was shown to have a moderate predictive power of development of a new upward trend.

The best Neural Network model successfully predicted 35% of all instances of "1" in Training and 31% in Testing. In this case, historic price information cannot be used as a sole predictor for development of new upward trend. However, it can be used as a guide to potential profitability and help with decisions of how much capital to allocate to each trade.

Time series approach predicts over 70% of successful trades and can be used as a basis for trading strategy, but its performance needs to be monitored to assure continuous accuracy.

Daily close prices chart below shows that most major reversals in daily trend were correctly captured by the model.

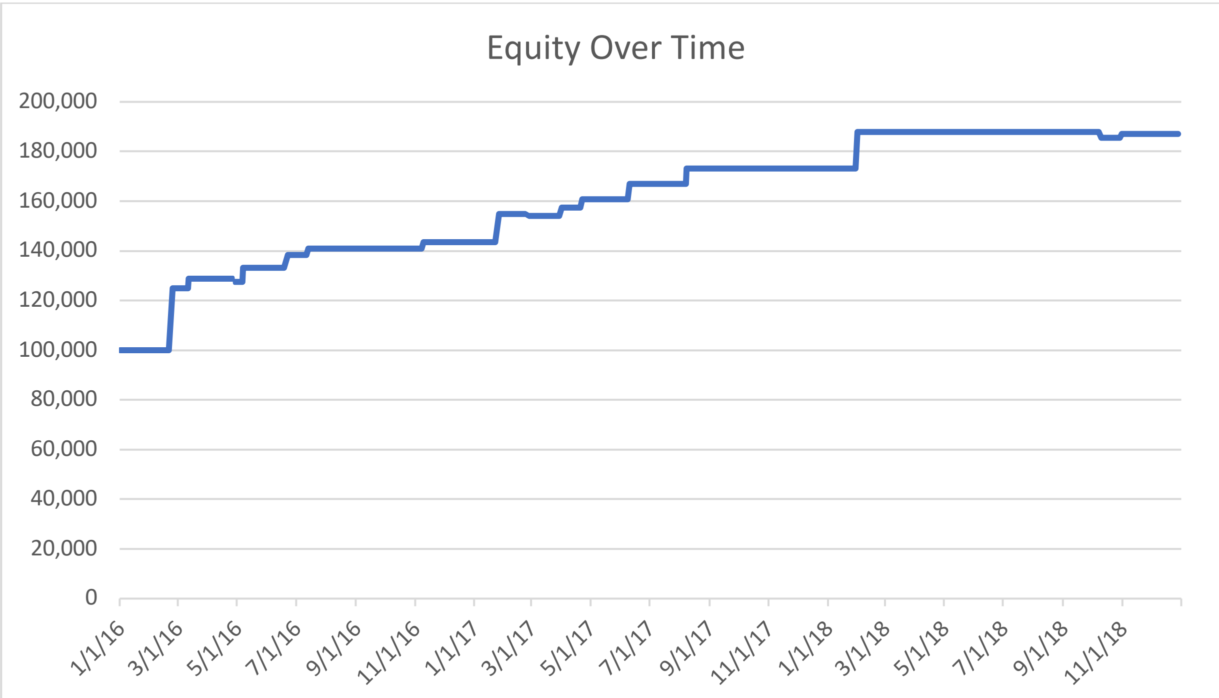
Figure 4.6: Plot of Predictions from BSTS for 2016-2018



False positives are distributed over long period of time and do not represent significant financial risk. False negatives are also distributed over long time and they did not present significant upside if trades were executed. Correctly predicted Non-events are excluded from the graph.

Assuming $100,000 of available capital at the beginning of 2016, application of the above logic would produce a build-up of equity shown on the chart below. As gold futures margin was $9,000 for the period, approximately 20% of available capital would be employed at any time if two gold futures were purchased every time BSTS model validated a signal. Equity build-up is provided on the graph 4.17. It is important to note that after producing 44% and 21% yearly returns in 2016 and 2017 correspondingly, return in 2018 was only 8% primarily due to the fact that only two trades were done in that year. The reason for such a small number of trades was a general downward trend for the most part of the year. Whilst capital was not employed for the most part of the year, it would potentially provide with opportunities with investments in other financial instruments or even earning some returns from a brokerage house which pays interest on unused balances. These earning opportunities as well as cost of capital were excluded from consideration in this paper.

Graph 4.7: Changes in Equity in 2016-2018



Variable importance

24 variables selected using IV and WOE methodologies appeared to have similar, if not better, predictive power as 123 variables. IV and WOE methodology therefore can be used regardless of the nature of the relationship between predictors and predicted variables. Individual results of the 24 variables selected are not possible to obtain due to black-box nature of Neural Networks.

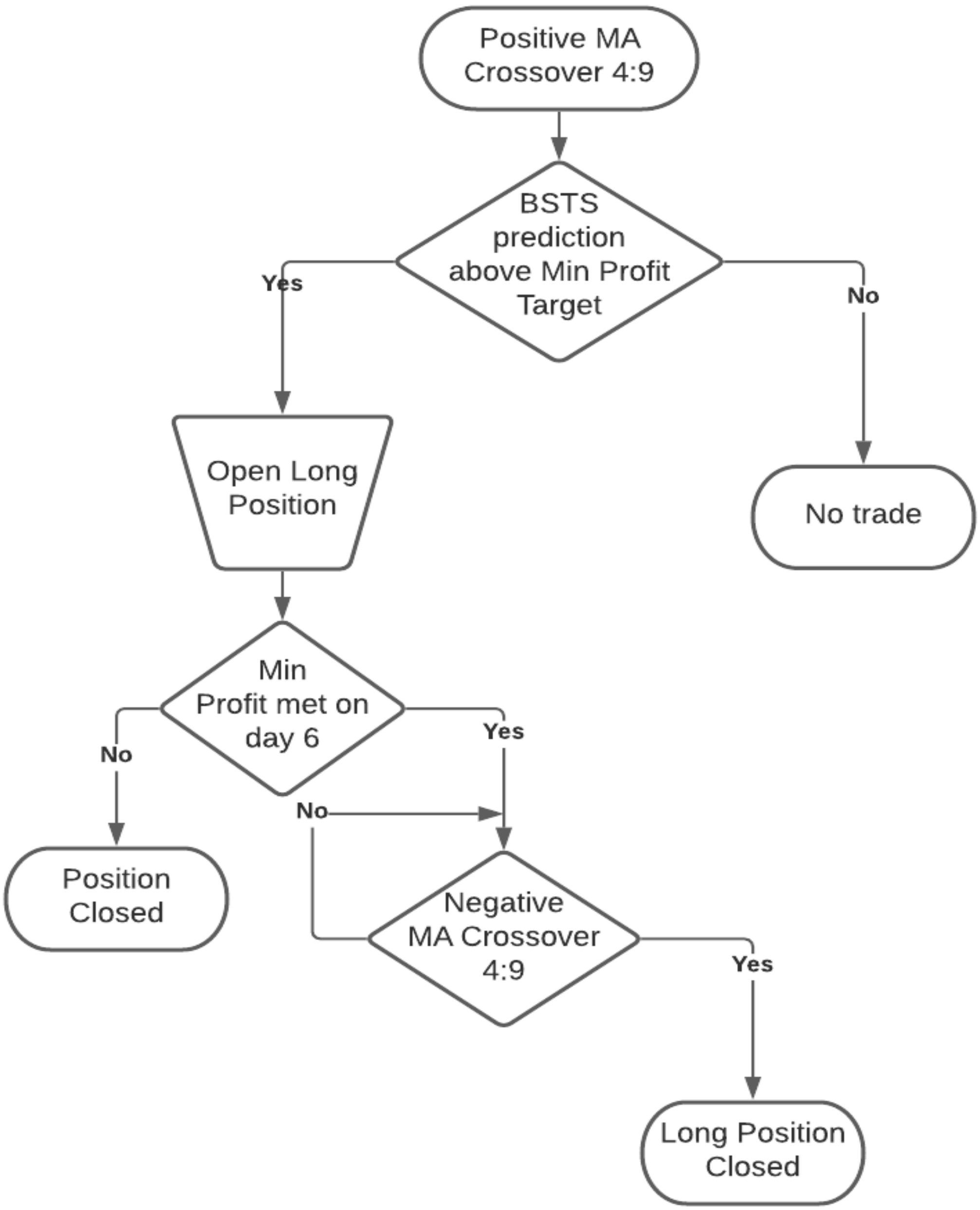
Time series approach identified a total of four variables that were used to produce optimal specification of the *state* with:

- two trend components
  - Local Trend of daily Close Price and
  - Local Trend of daily High Price

- Two dynamic regression components
    - 3-day lag of Close Price
    - 3-day Lag of High Price

Decision tree improved by application of BSTS model

Figure 4.8: Improved Decision Tree for Trading



4.4.3 Findings

This analysis faced numerous challenges. There was no existing research in and the methodologies used were experimental. Though accuracy of prediction of over 40% is definitely better than Random Choice at 30%, the overall number of events is not high enough for the model to be used as single decision-making tool.

This research helps to understand the relationship between historic data and development of new trends. Despite the small dataset, the predictive power that historic prices have on new trends has been proven. The models can be used as a guide to capital allocation by traders.

The best model from this research resulted in successful prediction of 33% of events with accuracy of 43%. Based on these metrics, we can reject the hypothesis that historic prices can be used to predict 90% of events with accuracy of above 50%.

4.4.4 Recommendations

Practical uses

The machine learning models in this research can be used as logic to capital allocation. Autoencoder model can be used to identify dates when probability of success is extremely low 8% and either exclude them from consideration or use a low-risk strategy such as calendar spread. If observation is not rejected by Autoencoder model, then NN can be used to allocate capital based on probability of success. As it stands observations with calculated probability below 0.5 have 26% likelihood of success, when those with probability above 0.5 have 42% likelihood. It means that the likelihood for observations from 0.5+ probability group to be profitable is 1.6 times higher. To achieve balanced approach to risk trader can buy 2 contracts every time probability is under 0.5 and 3 contracts when it is above 0.5.

Time series model can be used to make investment decisions on ongoing basis, by making trades every time the model suggests.

Future extensions

The research can be expanded to explore the same approach on other Futures contracts. Future studies can also further explore hidden layers structure of Neural Network and tuning of their hyperparameters. Due to the time series nature of the dataset, further extensions of Bayesian Structured Time Series and Bayesian Neural Networks should be explored. From portfolio management point of application of *state-space* models can be further explored for optimization of investments, especially when multiple opportunities are present at the same time.

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APPENDICES

Appendix A: List of created explanatory variables:

Variable	Description
mom1c	Close Price / Lag1 Close Price
mom4c	Close Price / Lag4 Close Price
mom9c	Close Price / Lag9 Close Price
mom15c	Close Price / Lag15 Close Price
mom30c	Close Price / Lag30 Close Price
mom60c	Close Price / Lag60 Close Price
mom90c	Close Price / Lag90 Close Price
ma.fut.spot4d	4 day moving average (future close price/spot close price)
ma.fut.spot9d	9 day moving average (future close price/spot close price)
ma.fut.spot15d	15 day moving average (future close price/spot close price)
ma.fut.spot30d	30 day moving average (future close price/spot close price)
ma.fut.spot60d	60 day moving average (future close price/spot close price)

ma.fut.spot90d	90 day moving average (future close price/spot close price)
op.cl.ratio	close price/open price
op.cl.4d.ma	4 day moving average (close price/open price)
op.cl.9d.ma	9 day moving average (close price/open price)
op.cl.15d.ma	15 day moving average (close price/open price)
op.cl.30d.ma	30 day moving average (close price/open price)
op.cl.60d.ma	60 day moving average (close price/open price)
op.cl.90d.ma	90 day moving average (close price/open price)
day.range.4day	(high price - low price)/4day moving average(high price - low price)
day.range.9day	(high price - low price)/9 day moving average(high price - low price)
day.range.15day	(high price - low price)/ 15 day moving average(high price - low price)
day.range.30day	(high price - low price)/ 30 day moving average(high price - low price)
day.range.60day	(high price - low price)/ 60 day moving average(high price - low price)
day.opInt.4day	OpenInterest/4day moving averageOpenInterest
day.opInt.9day	OpenInterest/9 day moving averageOpenInterest

day.opInt.15day	OpenInterest/ 15 day moving averageOpenInterest
day.opInt.30day	OpenInterest/ 30 day moving averageOpenInterest
day.opInt.60day	OpenInterest/ 60 day moving averageOpenInterest
mom.opInt1d	Open Interest/lag 1 OpenInterest
mom.opInt4d	Open Interest/lag 4 OpenInterest
mom.opInt9d	Open Interest/lag 9 OpenInterest
mom.opInt15d	Open Interest/lag 15 OpenInterest
mom.opInt30d	Open Interest/lag 30 OpenInterest
mom.opInt60d	Open Interest/lag 60 OpenInterest
op.cl.ratioXmom.opInt1d	(Close Price / Open Price) * (open interest / lag1 open interest)
mom.op.clXmom.opInt4d.ma	4 day moving average (Close Price / Open Price) * (open interest / lag1 open interest)
mom.op.clXmom.opInt9d.ma	9 day moving average (Close Price / Open Price) * (open interest / lag1 open interest)