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TRACING THE EVOLUTION OF FINANCIAL REPORTING FORECASTING: FROM HISTORICAL ROOTS TO MODERN PRACTICES IN STRATEGIC PLANNING AND DECISION-MAKING

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Financial reporting forecasting plays a pivotal role in the modern business landscape. The ability to accurately predict a company's financial performance is crucial for strategic planning, decision-making, and risk management. This article explores the evolution of financial reporting forecasting, tracing its historical development and examining the current practices that shape forecasting today.

Early Days of Financial Forecasting. Financial forecasting has its roots in the early accounting systems developed by ancient civilizations. Sumerians, Egyptians, and Babylonians were among the first to record transactions and maintain accounts. They used simple counting systems and clay tablets to document their economic activities, such as trade, taxes, and resource allocation. The double-entry bookkeeping system, which is still in use today, was developed in medieval Europe. This system involves record of financial activities. This innovation allowed merchants and business owners to track their financial performance, laying the foundation for financial forecasting. In 1494, Pacioli published the "Summa de Arithmetica, Geometria, Proportioni et Proportionalita," which included a detailed description of the double-entry bookkeeping system. His work became widely adopted across Europe and played a crucial role in the emergence of modern accounting practices. The Industrial Revolution in the late 18th and early 19th centuries led to the growth of large-scale businesses and the development of new financial instruments, such as stocks and bonds. This period marked the beginning of financial analysis, as business owners and investors sought to understand the financial performance of companies to make informed decisions.

Early Financial Analysis Techniques. Ratio analysis and trend analysis were among the first financial analysis techniques developed during this period. Ratio analysis involves comparing financial statement items to assess a company's liquidity, solvency, and profitability. For example, the current ratio (current assets divided by current liabilities) measures a company's ability to meet short-term obligations, while the debt-to-equity ratio (total debt divided by total equity) provides insights into a company's financial leverage. Trend analysis, on the other hand, involves studying historical financial data to identify patterns and project future performance. By examining trends in revenue, expenses, and net income, financial analysts could make informed predictions about a company's future prospects.

These early financial analysis techniques provided the foundation for the development of more advanced forecasting methods in the centuries that followed. As businesses grew more complex and financial markets became increasingly interconnected, the need for accurate financial forecasting became even more critical, leading to the development of sophisticated quantitative techniques and the widespread adoption of computers and technology in financial analysis. The Advent of Quantitative Forecasting Techniques. As financial forecasting evolved, analysts began to incorporate quantitative techniques to improve the accuracy of their predictions. Time series analysis, a statistical method for analyzing and forecasting data collected over time, emerged as a popular approach. Moving averages, a simple time series technique, involve calculating the average of a fixed number of data points to create a smoothed trend line. By removing short-term fluctuations, moving averages help analysts identify underlying trends and make better-informed forecasts. There are various types of moving averages, such as simple, weighted, and cumulative moving averages.

Exponential smoothing is another time series technique that gives more weight to recent data points in the calculation of the smoothed trend line. This approach is particularly useful for volatile data, as it can adapt more quickly to changes in the underlying trend.

Autoregressive Integrated Moving Average (ARIMA) Models. Building on the concepts of moving averages and exponential smoothing, ARIMA models were developed as a more sophisticated method for time series forecasting. ARIMA models consider three components: autoregression (AR), differencing (I), and moving average (MA). By combining these components, ARIMA models can account for trends, seasonality, and noise in the data, leading to more accurate forecasts.

However, despite their effectiveness, time series models have limitations when it comes to financial forecasting. They are primarily based on historical data and assume that past trends will continue into the future, which may not always hold true in dynamic financial markets.

Econometric Models. Econometrics emerged as a distinct field in the mid-20th century, combining economic theory, mathematics, and statistical techniques to analyze economic relationships and forecast financial variables. Econometric models provided a more comprehensive approach to financial forecasting, as they could account for the complex interactions between various economic factors.

The Application of Regression Analysis to Financial Forecasting. Regression analysis is a fundamental econometric technique used to estimate the relationships between variables. In financial forecasting, regression analysis helps analysts understand the impact of various factors, such as interest rates, inflation, and GDP growth, on financial variables like stock prices or corporate earnings. Multiple regression models, which consider several independent variables, are particularly useful in capturing the complex relationships between financial variables. For example, an analyst might use a multiple regression model to estimate the impact of changes in interest rates, consumer spending, and unemployment on a company's stock price. Multivariate Models and Vector Autoregression (VAR). As financial forecasting techniques continued to evolve, more advanced econometric models were developed to better capture the relationships between multiple variables. Multivariate models, taking into account their interdependencies.

VAR models have been widely adopted in financial forecasting, as they can accommodate complex relationships between financial variables and account for feedback effects. For example, a VAR model might be used to analyze the relationship between interest rates, inflation, and stock market returns, considering how changes in one variable can influence the others. The Impact of Computers and Technology on Financial Forecasting. The Introduction of VisiCalc, Lotus 1-2-3, and

Microsoft Excel. The development of electronic spreadsheet software in the late 1970s and 1980s revolutionized financial forecasting. VisiCalc, the first electronic spreadsheet program, was released in 1979 for the Apple II computer. It allowed users to perform complex calculations and manipulate financial data more efficiently than with traditional paper spreadsheets.

Following VisiCalc, Lotus 1-2-3 was introduced in 1983 and quickly became the dominant spreadsheet program for IBM-compatible PCs. In 1985, Microsoft released Excel, which eventually overtook Lotus 1-2-3 as the leading spreadsheet software. These electronic spreadsheets made it easier for financial analysts to organize, analyze, and forecast financial data, streamlining the forecasting process and improving accuracy.

The Democratization of Financial Forecasting and Analysis. The widespread adoption of electronic spreadsheets democratized financial forecasting and analysis by making sophisticated tools available to a broader range of users. Before the advent of spreadsheet software, financial forecasting was often limited to large corporations and financial institutions with the resources to employ specialized analysts. With the introduction of electronic spreadsheets, small businesses and individual investors gained access to powerful forecasting tools, enabling them to make more informed decisions and compete more effectively in the marketplace. The Development of Statistical Software. The rise of computers and technology also led to the development of specialized statistical software packages for financial forecasting. SAS (Statistical Analysis System), initially released in 1976, and SPSS (Statistical Package for the Social Sciences), first launched in 1968, were among the first widely adopted statistical software programs. These tools allowed analysts to perform advanced statistical analysis and forecasting more efficiently than with spreadsheet software alone. EViews, released in 1994, was specifically designed for econometric analysis and time series forecasting. It quickly gained popularity among financial analysts and researchers for its user-friendly interface and powerful forecasting capabilities.

The Growth of Open-Source Tools: R and Python. In recent years, open-source programming languages like R and Python have become increasingly popular for financial forecasting and analysis. R, released in 1993, and Python, first launched in 1991, both offer extensive libraries of statistical and machine learning packages, enabling analysts to develop custom forecasting models and perform advanced analysis.

The open-source nature of R and Python has fostered a vibrant community of users who contribute to the development of new packages and share knowledge through online forums and resources. This collaborative environment has accelerated the development of cutting-edge forecasting techniques and the adoption of advanced quantitative methods in financial analysis.

Modern Financial Forecasting Practices. The rapid advancement of machine learning and artificial intelligence (AI) has significantly impacted modern financial forecasting practices. These technologies have the potential to revolutionize financial analysis by automating complex tasks and uncovering patterns in large datasets that would be difficult for humans to identify.Machine learning algorithms, such as neural networks, support vector machines, and random forests, have been increasingly applied to financial forecasting tasks, including predicting stock prices, currency exchange rates, and credit risk. These algorithms can learn from historical data and adapt their predictions as new data becomes available, making them more flexible and accurate than traditional statistical methods.

Deep Learning and Natural Language Processing. Deep learning, a subset of machine learning, involves using artificial neural networks with many layers to learn complex patterns and representations from data. In recent years, deep learning has gained traction in financial forecasting, particularly in tasks that involve large amounts of unstructured data, such as financial news or social media posts.

Natural language processing (NLP), a branch of AI focused on understanding and interpreting human language, has also become increasingly relevant in financial forecasting. By analyzing textual

data, such as earnings reports, news articles, or analyst opinions, NLP algorithms can identify sentiment and other qualitative factors that may influence financial variables, complementing traditional quantitative analysis.

The Integration of Qualitative Approaches. While quantitative techniques have become increasingly sophisticated, qualitative approaches still play a vital role in modern financial forecasting. The Delphi method, for example, involves gathering expert opinions through a series of structured questionnaires to develop forecasts. This iterative process helps to reduce individual biases and converge on a consensus forecast. Incorporating expert opinions in financial forecasting can provide valuable insights into factors that are difficult to quantify, such as market sentiment, regulatory changes, or geopolitical risks. Combining quantitative methods with qualitative inputs can result in more comprehensive and accurate forecasts.

The Role of Management Judgment in Financial Forecasting. Management judgment is another important aspect of modern financial forecasting practices. While quantitative techniques and algorithms can provide valuable insights, they may not always capture the nuances of a company's specific situation, industry dynamics, or competitive landscape.

By incorporating management's expertise and knowledge of the business, analysts can refine their forecasts and ensure they are consistent with the company's strategic goals and objectives. Management judgment is particularly important in situations where data is limited or unreliable, or where external factors, such as market disruptions or regulatory changes, are likely to impact financial performance.

The Importance of Risk Management. In the wake of financial crises and market turbulence, risk management has become an increasingly important aspect of financial forecasting. Value at Risk (VaR), a widely used risk measure, estimates the potential loss in the value of a portfolio over a specified time horizon and at a given confidence level. VaR helps analysts and investors understand the risks associated with their investments and make informed decisions.

Stress testing, another critical risk management tool, involves simulating extreme market events or adverse scenarios to evaluate the potential impact on a company's financial performance or a portfolio's value. By understanding the potential consequences of such events, companies and investors can develop strategies to mitigate risks and enhance resilience. Scenario Analysis and Monte Carlo Simulation in Financial Forecasting. Scenario analysis and Monte Carlo simulation are also commonly used in modern financial forecasting practices to account for uncertainty and risk. Scenario analysis involves developing multiple forecasts based on different assumptions about key variables, such as economic growth, interest rates, or market conditions. This approach helps analysts understand the potential outcomes under various circumstances and make more robust decisions.

Monte Carlo simulation, on the other hand, is a computational technique that uses random sampling to estimate the probability distribution of potential outcomes. By running thousands of simulations with varying input values, Monte Carlo methods can provide a more comprehensive view of the potential risks and rewards associated with different financial decisions.

These risk management techniques have become essential components of modern financial forecasting practices, as they enable companies and investors to better understand the potential consequences of their decisions and develop strategies to navigate uncertain environments.

The Growing Importance of Data Quality and Governance. The increasing reliance on quantitative techniques and the growing volume of data available for financial forecasting have highlighted the importance of data quality and governance. Ensuring that the data used in financial forecasts is accurate, complete, and consistent is critical for generating reliable predictions.

Data management and cleaning are essential aspects of the forecasting process, as they involve identifying and correcting errors, removing duplicates, and filling in missing values. By maintaining high-quality data, financial analysts can enhance the accuracy and reliability of their forecasts and reduce the risk of making poor decisions based on faulty information.

Ethical Considerations and Regulatory Compliance. As financial forecasting practices continue to evolve, ethical considerations and regulatory compliance have become increasingly important. Financial analysts must ensure that their methods and data sources comply with relevant regulations, such as data privacy laws and industry-specific guidelines. Additionally, analysts must be aware of potential biases and ethical concerns related to the use of certain data sources or algorithms.

By adhering to ethical principles and regulatory requirements, financial analysts can maintain the integrity of their forecasts and build trust with stakeholders, including investors, regulators, and the public.

Challenges and Future Directions. Data Quality and Availability. One of the main challenges in financial forecasting is ensuring data quality and availability. As financial markets become more global and interconnected, the volume of data available for analysis continues to grow. However, this abundance of data can lead to issues related to data accuracy, consistency, and completeness. Financial analysts must constantly evaluate their data sources and develop robust data management processes to maintain high-quality inputs for their forecasts.

Model Complexity and Overfitting. As quantitative techniques become more advanced, there is a risk that financial forecasting models may become overly complex and difficult to interpret. Overly complex models may also be prone to overfitting, which occurs when a model is excessively tailored to the historical data and performs poorly on new, unseen data. To overcome this challenge, analysts need to strike a balance between model complexity and interpretability, ensuring that their forecasts are both accurate and understandable.

Non-Stationarity and Structural Breaks. Financial time series data are often characterized by non-stationarity and structural breaks, which can pose challenges for financial forecasting. Non-stationarity refers to the changing statistical properties of a time series over time, while structural breaks are abrupt changes in the underlying data-generating process. These characteristics can make it difficult to develop accurate and stable forecasting models, as they require constant monitoring and adjustments to account for changes in the data.

Integration of Qualitative and Quantitative Approaches. Another challenge in financial forecasting is the integration of qualitative and quantitative approaches. While quantitative methods can provide valuable insights, they may not capture all relevant factors, particularly those that are difficult to quantify or measure. Incorporating qualitative inputs, such as expert opinions or management judgment, can help address these gaps and improve forecast accuracy. However, finding the right balance between qualitative and quantitative inputs and developing methods to effectively combine them remains a challenge.

Future Directions in Financial Forecasting. Machine learning and AI are expected to play an increasingly important role in financial forecasting as these technologies continue to advance. Researchers are continually developing new algorithms and techniques to improve the accuracy and efficiency of financial forecasting models. These advancements will likely lead to the development of more sophisticated forecasting tools that can better adapt to changing market conditions and provide more accurate predictions.

Increased Adoption of Alternative Data Sources. As financial forecasting practices continue to evolve, the use of alternative data sources is expected to become more widespread. Alternative data refers to non-traditional data sources, such as satellite imagery, social media sentiment, or web traffic data,that can provide valuable insights into financial variables. By incorporating alternative data into their analysis, financial analysts can gain a more comprehensive understanding of the factors influencing financial performance and improve the accuracy of their forecasts.Enhanced Integration of Risk Management Techniques. Risk management will continue to be a critical aspect of financial forecasting, as markets become more volatile and uncertain. Financial analysts will need to develop more robust risk management techniques and integrate them into their forecasting processes to better understand the potential consequences of their decisions and navigate uncertain environments.

Ethical and Regulatory Considerations. As financial forecasting practices continue to advance, ethical and regulatory considerations will become increasingly important. Financial analysts will need to be aware of potential biases and ethical concerns related to the use of certain data sources or algorithms, and ensure that their methods comply with relevant regulations. By adhering to ethical principles and regulatory requirements, financial analysts can maintain the integrity of their forecasts and build trust with stakeholders.

Conclusion: The Evolution of Financial Reporting Forecasting. Throughout history, financial forecasting has evolved significantly as new methods, technologies, and data sources have emerged. From the early days of financial forecasting, which relied primarily on basic financial ratios and expert opinions, to the advent of quantitative techniques and the impact of computers and technology, the field has seen tremendous growth and change.

In recent years, modern financial forecasting practices have incorporated advanced quantitative techniques, such as machine learning and AI, while continuing to recognize the importance of qualitative approaches, expert opinions, and management judgment. Risk management has also become an increasingly critical component of financial forecasting, as analysts and decision-makers strive to navigate uncertain and volatile markets.

As we look to the future of financial forecasting, the field will likely continue to face challenges and opportunities in equal measure. Ensuring data quality and availability, balancing model complexity with interpretability, and integrating qualitative and quantitative approaches will be ongoing concerns for financial analysts. At the same time, the continued advancement of machine learning, AI, and alternative data sources will drive innovation and improve forecasting capabilities. Ethical and regulatory considerations will play an increasingly important role in shaping the future of financial forecasting, as analysts and decision-makers must navigate a complex landscape of data privacy laws, industry-specific guidelines, and potential biases in data and algorithms.

In conclusion, the evolution of financial reporting forecasting reflects a constant process of adaptation and innovation in response to changing market conditions, technological advancements, and shifting regulatory environments. By embracing these challenges and continually refining their forecasting techniques and practices, financial analysts can contribute to more informed decision-making and play a vital role in shaping the future of finance.

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