Intelligent Systems Reference Library 254

Leandros A. Maglaras
Sonali Das
Naliniprava Tripathy
Srikanta Patnaik *Editors*

Machine Learning Approaches in Financial Analytics

Springer

Intelligent Systems Reference Library

Volume 254

The aim of this series is to publish a Reference Library, including novel advances and developments in all aspects of Intelligent Systems in an easily accessible and well structured form. The series includes reference works, handbooks, compendia, textbooks, well-structured monographs, dictionaries, and encyclopedias. It contains well integrated knowledge and current information in the field of Intelligent Systems. The series covers the theory, applications, and design methods of Intelligent Systems. Virtually all disciplines such as engineering, computer science, avionics, business, e-commerce, environment, healthcare, physics and life science are included. The list of topics spans all the areas of modern intelligent systems such as: Ambient intelligence, Computational intelligence, Social intelligence, Computational neuroscience, Artificial life, Virtual society, Cognitive systems, DNA and immunity-based systems, e-Learning and teaching, Human-centred computing and Machine ethics, Intelligent control, Intelligent data analysis, Knowledge-based paradigms, Knowledge management, Intelligent agents, Intelligent decision making, Intelligent network security, Interactive entertainment, Learning paradigms, Recommender systems, Robotics and Mechatronics including human-machine teaming, Self-organizing and adaptive systems, Soft computing including Neural systems, Fuzzy systems, Evolutionary computing and the Fusion of these paradigms, Perception and Vision, Web intelligence and Multimedia.

Indexed by SCOPUS, DBLP, zbMATH, SCImago.

All books published in the series are submitted for consideration in Web of Science.

Leandros A. Maglaras · Sonali Das ·
Nalinipravа Tripathy · Srikanta Patnaik
Editors

Machine Learning Approaches in Financial Analytics

Springer

Editors
Leandros A. Maglaras
Edinburgh Napier University
Edinburgh, UK

Naliniprava Tripathy
Indian Institute of Management
Shillong, India

Sonali Das
Department of Business Management
University of Pretoria
Hatfield, South Africa

Srikanta Patnaik
Institute of Management and Technology
Bhubaneswar, Odisha, India

ISSN 1868-4394 ISSN 1868-4408 (electronic)
Intelligent Systems Reference Library
ISBN 978-3-031-61036-3 ISBN 978-3-031-61037-0 (eBook)
https://doi.org/10.1007/978-3-031-61037-0

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

Welcome to *Machine Learning Approaches in Financial Analytics*. In an era where technology is rapidly transforming every industry, the fusion of machine learning and finance has created a powerful synergy that is reshaping how we understand, predict, and navigate the intricate landscape of financial markets.

This book serves as a comprehensive guide to the intersection of machine learning and finance. It's designed for both seasoned finance professionals seeking to integrate the latest technological advancements into their work and for data scientists eager to delve into the intricate world of financial analytics.

The financial world has always been a realm of complexity, marked by volatility, uncertainty, and dynamic interconnectedness. Traditional models and tools have often struggled to capture the multifaceted nature of this domain. However, machine learning techniques offer a paradigm shift, providing the capability to process vast amounts of data, identify patterns, and generate insights that were previously unimaginable.

Throughout the chapters of this book, we explore the fundamental principles of machine learning and how they can be applied to tackle a myriad of financial challenges. From predictive modeling, risk assessment, algorithmic trading, portfolio optimization, fraud detection, to customer segmentation, the potential applications are boundless.

Readers will embark on a journey that begins with foundational concepts and gradually progresses to advanced methodologies, allowing for a comprehensive understanding of both the financial and technological aspects. Real-world case studies and practical examples will illustrate how machine learning algorithms are transforming the way we perceive, analyze, and strategize within financial markets.

This book aims to bridge the gap between the financial and technological realms, catering to those who seek to harness the power of machine learning in their financial endeavors. By providing a deeper comprehension of the underlying principles and methodologies, readers will be equipped to make informed decisions, develop innovative strategies, and ultimately leverage the potential of machine learning in the realm of finance.

We sincerely hope that *Machine Learning Approaches in Financial Analytics* serves as a valuable resource in your quest to explore the dynamic landscape where finance and technology converge. May this knowledge empower you to navigate the complexities of financial markets with confidence, enabling you to unlock new opportunities and insights in the realm of financial analytics.

Best wishes on your journey into the world of machine learning in financial analytics.

Bhubaneswar, India Srikanta Patnaik

Editorial

In today's fast-paced, data-driven world, the realms of finance and technology are converging like never before. Machine learning, a subset of artificial intelligence, has emerged as a game-changer in the world of financial analytics. The integration of advanced algorithms and predictive models has revolutionized the way financial institutions, investors, and professionals analyse and predict market trends, manage risk, and make critical decisions. In this edited volume, *Machine Learning Approaches in Financial Analytics*, we dive deep into this exciting and rapidly evolving field, providing a comprehensive guide for individuals looking to leverage the power of machine learning in the finance industry.

The financial industry is no stranger to technological innovation, and machine learning is the latest breakthrough in this ongoing transformation. From algorithmic trading and portfolio management to credit risk assessment and fraud detection, machine learning techniques are being harnessed to enhance efficiency, reduce costs, and improve accuracy in decision-making. Our book unravels this financial revolution, making complex concepts accessible to both novices and experts, as we explore the intersection of finance and artificial intelligence.

Key Features

Foundations: We start by building a strong foundation in machine learning, ensuring that readers are equipped with the knowledge they need to navigate the complexities of financial analytics. This part provides a gentle introduction to machine learning concepts, algorithms, and models.

Tools and Techniques: To assist professionals in applying machine learning to their work, we offer practical guidance, including coding examples, case studies, and insights from industry experts. The book bridges the gap between theory and practice, helping readers translate knowledge into action.

Risk Assessment and Ethical Considerations: In an era defined by market volatility and economic uncertainty, managing risk is paramount. Machine learning offers powerful tools for assessing, mitigating, and predicting risks in the financial sector. Our book delves into these risk management strategies, providing insights into stress testing, credit scoring, and fraud detection.

As with any transformative technology, machine learning in finance comes with ethical considerations. We address these concerns, discussing topics like bias in algorithms, data privacy, and regulatory compliance to ensure that readers have a well-rounded understanding of the impact of machine learning in the financial industry.

Real-World Applications: The heart of our book lies in the exploration of real-world applications of machine learning in finance. From forecasting stock prices and managing investment portfolios to optimizing trading strategies, we illustrate how machine learning is transforming these critical financial processes.

The final part explores the future of machine learning in financial analytics, predicting upcoming trends, and suggesting areas where further innovation is likely to occur.

Chapter 1 entitled "Introduction to Optimal Execution" by Makoto Shimoshimizu aims to overview how the current financial market works and how one can analyse and build the algorithms for an optimal trading strategy.

Chapter 2 entitled "Python Stack for Design and Visualization in Financial Engineering" authored by Jayanth R. Varma and Vineet Virmani highlighted the power of the Python stack for designing graphical user interfaces for engineering structured product solutions by visualizing their payoffs and prices in a web browser.

Chapter 3 entitled "Neurodynamic Approaches to Cardinality-Constrained Portfolio Optimization" authored by Man-Fai Leung and Jun Wang focuses on the integration of neurodynamic optimization and cardinality-constrained portfolio optimization with fruitful results and significant breakthroughs.

Chapter 4 entitled "Fully Homomorphic Encrypted Wavelet Neural Network for Privacy-Preserving Bankruptcy Prediction in Banks" by Syed Imtiaz Ahamed et al. proposes a fully homomorphic encrypted wavelet neural network to protect privacy and at the same time not compromise on the efficiency of the model.

Chapter 5 by Marco Piccolo and Francesco Vigliarolo is titled as "Tools and Measurement Criteria of Ethical Finance Through Computational Finance" which demonstrates how computational finance itself can be treated in terms of social reasoning.

Chapter 6 by Gaurav Kumar and Arun Kumar Misra entitled "Data Mining Techniques for Predicting the Non-performing Assets (NPA) of Banks in India" presents the findings of a formal attempt to explain NPA variations from 2005 to 17.

The author of the Chap. 7 entitled "Multiobjective Optimization of Mean–Variance-Downside-Risk Portfolio Selection Models" is Georgios Mamanis. He experimentally investigated the out-of-sample performance of three multiobjective portfolio optimization models, namely Mean-Variance-VaR, Mean-Variance-LPSD (LPSD: Lower Partial Standard Deviation) and Mean-Variance-Skewness.

Chapter 8 by Simrat Kaur and Anjali Munde entitled "Bankruptcy Forecasting of Indian Manufacturing Companies Post the Insolvency and Bankruptcy Code 2016 Using Machine Learning Techniques" conducted a comparative analysis of numerous bankruptcy predictive models in order to recommend the optimal model with the highest accuracy for bankruptcy prediction.

Chapter 9 entitled "Ensemble Deep Reinforcement Learning for Financial Trading" is authored by Mendhikar Vishal et al. proposed a couple of ensemble methods that use a few deep reinforcement learning (DRL) architectures to train on dynamic markets and learn complex trading strategies to achieve maximum returns on investments.

Chapter 10 entitled "Bibliometric Analysis of Digital Financial Reporting" authored by Neha Puri and Vikas Garg examines the literature that has been written about digital financial reporting between 2011 and 2022 using descriptive research.

Chapter 11 entitled "The Quest for Financing Environmental Sustainability in Emerging Nations: Can Internet Access and Financial Technology Be Crucial?" by Ekundayo Peter Mesagan et al. analyses the role of internet access and financial technology adoption to drive the quest for environmental sustainability financing in emerging nations with a special focus on African countries.

Chapter 12 by Sidhartha Harichandan et al. entitled "A Comprehensive Review of Bitcoin's Energy Consumption and Its Environmental Implications" forecasts the future of bitcoin mining and its influence on sustainability.

Chapter 13 entitled "Emerging Economies: Volatility Prediction in the Metal Futures Markets Using GARCH Model" by Ravi Kumar et al. aims to study the volatility and its prediction using the GARCH (1, 1) model in the metal futures of two emerging economies, India and China.

Chapter 14 by Mekar Satria Utama et al. identify the elements steering compliance intentions, various influencing variables need exploration in their chapter entitled "Constructing a Broad View of Tax Compliance Intentions Based on Big Data".

Chapter 15 by Suzan Dsouza and Ajay Kumar Jain is titled as "Influence of Firm-Specific Variables on Capital Structure Decisions: An Evidence from the Fintech Industry" examines the influence of firm-specific variables that determine the Capstr decisions of firms from the fintech industry.

Chapter 16 by Vasilios N. Katsikis et al. entitled "A Weights Direct Determination Neural Network for Credit Card Attrition Analysis" utilizes neural networks to address the challenges of credit card attrition since they have found great application in many classification problems.

Chapter 17 entitled "Stock Market Prediction Using Machine Learning: Evidence from India" is authored by Subhamitra Patra et al. They predict the movements of the Indian stock markets over 2000–2022 and observes certain dynamism in both the actual and predicted trends of the Indian stock markets.

Chapter 18 by Riza Demirer et al. is titled as "Realized Stock-Market Volatility: Do Industry Returns Have Predictive Value?", where they utilized a machine learning technique known as random forests to compute predictions of realized (good and bad) stock-market volatility, and showed that incorporating the information in lagged industry returns can help improve out-of-sample predictions of aggregate stock-market volatility.

Chapter 19 entitled "Machine Learning Techniques for Corporate Governance" by Deepika Gupta seeks to find answers and solutions by exploring new thoughts not only on performance measures and theories of corporate governance but also on new research methods through machine learning techniques.

Chapter 20 entitled "Machine Learning Approaches for Forecasting Financial Market Volatility" by Itishree Behera et al. extends the discussion of forecasting financial market volatility using machine learning techniques to the real estate market context.

Chapter 21 by Sai Krishna Vishnumolakala et al. entitled "Deep Learning Models in Finance: Past, Present, and Future" provides a comprehensive overview of the current state of the art in DL models for financial applications.

Last but not least, Chap. 22 entitled "New Paradigm in Financial Technology Using Machine Learning Techniques and Their Applications" is authored by Deepti Patnaik and Srikanta Patnaik which delves into the examination of the impact of machine learning approaches in assessing credit risk and finance. It scrutinizes the limitations of recent studies and explores emerging research trends in this domain.

Machine Learning Approaches in Financial Analytics is a comprehensive guide for anyone seeking to navigate the dynamic intersection of finance and technology. The integration of machine learning into financial analytics has the potential to redefine the industry, offering new opportunities for growth, risk management, and financial well-being. It combines theoretical insights with practical applications, ethical considerations, and expert perspectives to offer a holistic understanding of the impact and potential of machine learning in finance. This book will empower its readers to make informed, data-driven decisions in the dynamic world of financial analytics.

Whether one is a finance professional looking to gain a competitive edge, an investor seeking better decision-making tools, or a student eager to explore the forefront of financial technology, this book provides the knowledge and insights you need to succeed in this exciting and transformative field. As you embark on your journey through these pages, you will not only master the tools and techniques but also gain a profound understanding of how machine learning is reshaping the future of finance.

Bhubaneswar, India Srikanta Patnaik

Contents

Part I
Foundations

Chapter 1
Introduction to Optimal Execution

Makoto Shimoshimizu

Abstract The developments in electronic markets have led to the diversification of trading activity, and traders need to manage the liquidity risk carefully. This problem is called the optimal execution problem and has become a significant issue among financial mathematicians, economists, and practitioners. This chapter aims to overview how the current financial market works and how one can analyze and build the algorithms for an "optimal execution strategy." The first section gives a review of current financial markets, which leads to the basics for constructing a model of optimal execution from the viewpoints of market microstructure. In particular, I clarify the system of the "limit order book," which includes an exposition about how traders place orders and influence the market. Also, this section presents the basic concepts of "large trader" and "market impact," on top of which most execution models are built. The succeeding sections explain how one can incorporate market impact in modeling and formulate an execution problem through a fundamental model posed by Almgren and Chriss (J. Risk 3:5–39, 2000 [2]). I then describe an extensive model with a moderate change in market impact modeling, discussed in Ohnishi and Shimoshimizu (Quant. Financ. 20:1625–1644, 2020 [35]). These models embody the foundation of algorithms for optimal execution strategies.

1.1 Overview: Financial Market and Execution Problem

1.1.1 Electronic Market and System Transition

Various ways of trading are available to a preponderance of a trading market since the structure of trading systems diverges in different directions. As an example of a wide variety of electric trading platforms, *algorithmic trading* has emerged in these decades, and the so–called *high–frequency trading* (*HFT*) with computer systems, which typifies algorithmic trading, significantly influences the financial market.

M. Shimoshimizu (✉)
Department of Industrial and Systems Engineering, Tokyo University of Science, Tokyo, Japan
e-mail: shimosshi1q94@gmail.com

L. A. Maglaras et al. (eds.), *Machine Learning Approaches in Financial Analytics*,
Intelligent Systems Reference Library 254,
https://doi.org/10.1007/978-3-031-61037-0_1

The last three decades have witnessed a huge (and worldwide) change in the trading system on stock exchanges. For example, as stated in [33], the regulatory development of the HFT was accelerated over the 1990s for the financial market to be more competitive among market participants. The related regulation, Regulation ATS (alternative trading systems; Reg ATS) in 2000, was enforced in the U. S. for the sorts of non–exchange competitors to be able to enter the marketplace.[1]

In light of the emergence of MiFID in 2007, considerable concerns about the so-called *dark pool* have arisen among practitioners and researchers. A dark pool is a (private) securities trading exchange where traders can use an uninformed order book and matching engine. Since the MiFID was enforced in Europe, institutional traders such as pension fund manager rapidly used dark pools, where the trading of a large block of orders are not informed to the market participants.

According to [24], although traders did not often use high-frequency trading (HFT) around 2000, HFTs have accounted for 20 percent of the total trading volume in the market since the mid-2000s (until 2019). The *volume-weighted average price* (*VWAP*) or *time-weighted average price* (*TWAP*) strategy was the mainstream of algorithmic trading in the early 2000s. The VWAP, denoted by P_{VWAP}, is a benchmark as the average price weighted by the relative volume over the trading time window:

$$P_{\mathrm{VWAP}} := \frac{\sum_{i=1}^{n} P_i V_i}{\sum_{i=1}^{n} V_i}, \tag{1.1}$$

where P_i is the asset price at time n. The VWAP strategy aims to maintain the price dynamics as the VWAP via one's own trading activity. The TWAP, denoted by P_{TWAP}, is a benchmark as the average price of a given number of trades, say n, over the trading time window:

$$P_{\mathrm{TWAP}} := \frac{1}{n} \sum_{i=1}^{n} P_i. \tag{1.2}$$

The VWAP and TWAP are not realized until the end of the trading horizon. Thus, traders generally consider the historical VWAP and TWAP as the benchmark. However, using some liquidity-seeking algorithms has become more common since the mid-2000s (until 2019). These facts underscore the importance of analyzing algorithmic trading or HFT which financial market traders have heavily relied on for

[1] The Regulation National Market System (Reg NMS) in 2007 and Market in Financial Instrument Directive (MiFID) in 2007, enforced in the U.S. and Europe, respectively, brought about a negative outcome. Even though these regulations are designed for encouraging new competition and trading venues, equity markets in the U.S. and Europe are fragmented since tradings spread out among various exchanges and financial markets.

more than a decade. The development of the trading system facilitates an increasing number of studies encompassing a field such as market impact modeling, or (optimal) execution problem.

1.1.2 Large Trader and Market (Price) Impact

There is a growing awareness among academic researchers or practitioners that some institutional traders called *large traders* cause the *market impact* (or so-called *price impact*) through their trades.[2] A life insurance company, trust company, or company that manages pension funds exhibit typical examples of such traders of great importance. Large traders recognize these market impacts as *liquidity risk*. They can reduce the liquidity risk by splitting their order into small sizes over the course of the trading epoch. Conversely, submitting small pieces of order gradually may expose large traders to the risk of future price fluctuation. Thus, every large trader has to pay attention to two distinct facets. The first ingredient is the *liquidity risk* which arises owing to the large orders he/she submits, and the *price risk* corresponding to the price fluctuations in the future. In the literature, the generally accepted use of the term *execution* refers to buy/sell orders submitted by large traders. Developments in trading technology for algorithmic trading or HFT have attracted a growing body of research regarding *execution problems*. The *optimal execution problem* refers to the one focusing on a large trader who aims to *minimize an expected trading cost* or *maximize an expected utility from his/her wealth*.

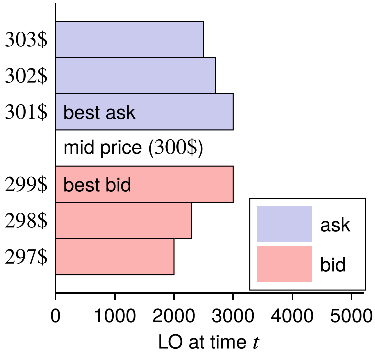
1.1.2.1 Order Type and Limit Order Book

The mechanism of how the market impact occurs is captured via the information obtained from the so-called limit order book. A *limit order book* (commonly abbreviated as *LOB*) is a set of information including volumes of buy/sell orders, and the price at which the volume is submitted by traders. All market participants can access the information about LOB.

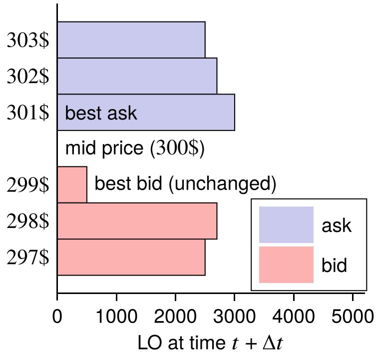
A trader can select how to submit orders from the following two ways: market order and limit order.[3] A *market order* (*MO*) is a one used by traders to execute buy/sell orders *immediately* after the order submission. A *limit order* (*LO*) is, on the contrary, aimed at executing buy/sell orders *at the price which the trader prefers to trade*. One of the main differences between the two orders is the fact that MOs are

[2] As a current stream, the impact caused by large traders as well as other traders is called the *market impact* rather than the price impact. Therefore, the author consistently uses the word *market impact* in what follows.

[3] The types of orders a trader can use are categorized into more classes (e.g., cancellation, dark-pool, and so on). Here our aim is to illustrate a basic concept of how the market works and how a market impact can arise. Readers can refer to [10, 22, 47] for more details.



(a) State of the LOB at time t.



(b) State of the LOB at time $t + \Delta t$.

Fig. 1.1 Example of submiting a sell market order. Assume that the volume of best bid at time t is 3000 (units) at the best bid price 299$. When a trader submits *2500* (units of) volumes of sell market orders, the LO at the best bid price is firstly executed. Since the volume of orders placed at the best bid price is *less* than the market orders submitted by the trader, ***the best bid price does not change***. The best bid price at time $t + \Delta t$ thus remains 299$ and the execution price also remains unchanged for the market order. Also, *any market impacts does not occur*

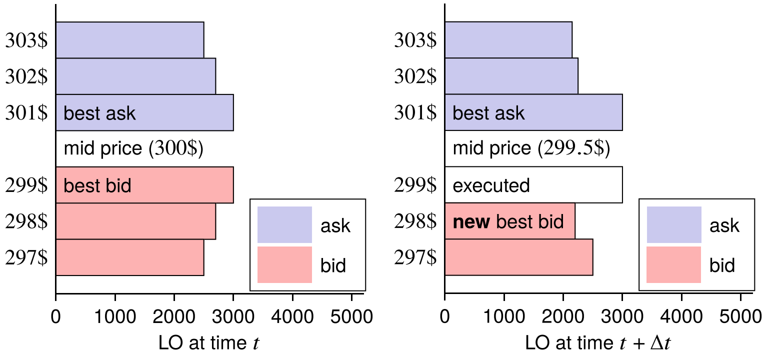
executed for certain, although LOs are not certainly executed. The feature of MOs and LOs will be illustrated from Figs. 1.1, 1.2, 1.3 and 1.4.[4]

Some terminology expressing the LOB precedes at first. The term *bid* (*ask*, respectively) has been applied to each buy (sell) LO. The price at which each buy (sell) order is placed is referred to as *bid price* (*ask price*). In particular, the term *best bid price* (*best ask price*) defines the highest (lowest) price of the bid (ask) price. A trader submits an LO by designating the order type (buy/sell), the volume, and the price at which the trader wants the orders to be executed. The term *LOB* is generally understood to mean all the information about these features as well as the time each order is placed. If an opposite LO at a price less than the best bid price or larger than the best ask price comes into the market, the buy/sell transaction matches and the LO vanishes in the LOB. Let us denote the best bid price and best ask price at time t by P_t^{b} and P_t^{a}, respectively. Then, the *mid-price*, expressed as P_t^{mid}, is defined as

$$P_t^{\mathrm{mid}} := \frac{P_t^{\mathrm{b}} + P_t^{\mathrm{a}}}{2}. \tag{1.3}$$

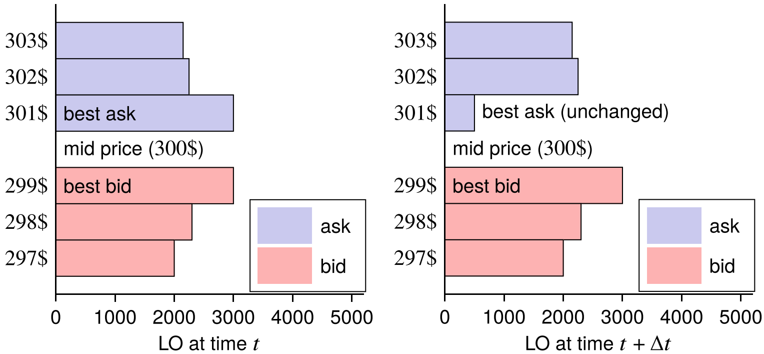
The minimum price increment that all traders can submit orders is called *tick size*. A change in the tick size influences the trading activity of market participants. (For the details, see, for example [10, 22, 47].)

[4] The tick size is assumed to be 1$ in Figs. 1.1, 1.2, 1.3 and 1.4. The horizontal axis denotes the volume of orders on the LOB and the vertical axis the price at which each order is placed (as LOs).



(a) State of the LOB at time t. (b) State of the LOB at time $t + \Delta t$.

Fig. 1.2 Example of submiting a sell market order. Assume that the volume of best bid at time t is 3000 (units) at the best bid price 299$. When a trader submits *3500* (units of) volumes of sell market orders, the LO at the best bid price is firstly executed. Since the volume of orders placed at the best bid price is *larger* than the market orders submitted by the trader, ***the best bid price changes***. The best bid price at time $t + \Delta t$ thus moves to the next ask price (i.e., decreases) and becomes 298$. The execution price also changes for the market order and the *market impact occurs*

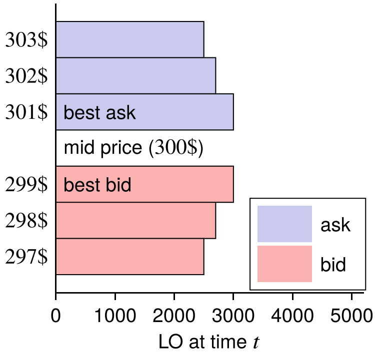


(a) State of the LOB at time t. (b) State of the LOB at time $t + \Delta t$.

Fig. 1.3 Example of submiting a buy market order. Assume that the volume of best ask at time t is 3000 (units) at the best ask price 301$. When a trader submits *2500* (units of) volumes of buy market orders, the LO at the best ask price is firstly executed. Since the volume of orders placed at the best ask price is *less* than the market orders submitted by the trader, ***the best ask price does not change***. The best ask price at time $t + \Delta t$ thus remains 301$ and the execution price also remains unchanged for the market order. Also, *any market impacts does not occur*.

1.1.2.2 Types of Market Impact

We can categorize the market impact mentioned above into three types: temporary, permanent, and transient market impact. The *temporary* (*market*) *impact* is defined to stand for the part vanishing before the next trading due to the recovery of (limited) market liquidity. On the other hand, the part of the market impact that remains at the



(a) State of the LOB at time t.

(b) State of the LOB at time $t + \Delta t$.

Fig. 1.4 Example of submiting a buy market order. Assume that the volume of best ask at time t is 3000 (units) at the best ask price 301$. When a trader submits *3500* (units of) volumes of buy market orders, the LO at the best ask price is firstly executed. Since the volume of orders placed at the best ask price is *larger* than the market orders submitted by the trader, ***the best ask price changes***. The best ask price at time $t + \Delta t$ thus moves to the next ask price (i.e., increases) and becomes 302$. The execution price also changes for the market order and the *market impact occurs*

next trading time is referred to as the *permanent* (*market*) *impact*. Moreover, when the temporary impact dissipates over the course of the trading horizon, we call the market impact the *transient* (*market*) *impact*.[5] Figure 1.5 illustrates the basic concept explained above.

Assume that a market (or quoted) price is given by P_t. Since a large trader executes a large number of orders denoted by q_t, the *execution price* (that corresponds to the real trading price) goes up to some degree and becomes $P_t + \lambda_t q_t$. Here $\lambda_t q_t$ denotes the market impact caused by the submission of the large trader (under the assumption of a linear market impact model). After the execution, the market price goes down to some degree due to the liquidity provision from the market participants (e.g., market makers, noise traders, and so on).[6] The impact that does not affect the (market) price at the next trading time (corresponding to $\lambda_t q_t \alpha_t$ in Fig. 1.5) is the temporary impact. The impact that affects the (market) price at the next trading time (corresponding

[5] The definition of each kind of market impact may be different from that of other literature. The above definition stems from the assumption that the market impact is decomposed into a temporary part and a permanent one. Some literature, such as [8, 17], empirically show that the market impact has transient properties. In the following, each market impact is abbreviated as temporary impact, permanent impact, and transient impact, respectively.

[6] We can classify the types of traders as follows:

1. *Noise Traders*: trading by economic fundamentals outside the exchange;
2. *Informed Traders*: traders seeking profit by leveraging information unreflected in market prices and trading assets in anticipation of future price movement;
3. *Market Makers*: professional traders seeking profit by facilitating exchange and exploiting their skills.

.

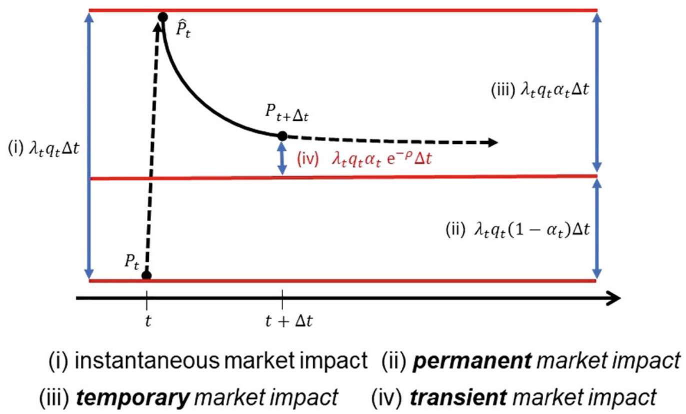


Fig. 1.5 Illustration of temporary, permanent, and transient market impact (in the case of buy MO)

to $\lambda_t q_t (1-\alpha_t)$ in Fig. 1.5) is the permanent impact. Moreover, the transient impact describes a residual effect of past temporary impacts caused by the large trader (and other market participants). The formulation of temporary, permanent, and transient impacts is set to become a vital factor in analyzing optimal execution problems.

1.1.2.3 Arbitrage and Market Impact Function

An *arbitrage* opportunity is a key ingredient for market participants and is attracting considerable interest from the viewpoints of both academicians and practitioners. Arbitrage trading is a practical method that attempts to obtain profit by focusing on the difference in prices and taking a position to buy an undervalued investment and sell an overvalued one. Particularly, the existence of a *dynamic arbitrage* is recognized as one of the important aspects of a financial market. The notion of dynamic arbitrage is defined via the notion of round-trip trading as follows.

Definition 1 (*Round Trip Trading and Dynamic Arbitrage*) A *round-trip trading* is a method of trading on $[0, T]$ (or $0 = t_0 < t_1 < \cdots < t_{n-1} < t_n = T$) that satisfies $\sum_{t=0}^{T} q_t = 0$. A *dynamic arbitrage* is an opportunity of arbitrage that makes use of a round trip profitable from an expected cost minimization point of view. To be precise, a dynamic arbitrage exists if and only if a trading strategy, which q_t for time $t \in [0, T]$ (or $0 = t_0 < t_1 < \cdots < t_{n-1} < t_n = T$) consists of, exists that satisfies $\sum_{t=0}^{T} q_t = 0$ and

$$\mathbb{E}\Big[W_T\Big] \geq W_0, \tag{1.4}$$

where W_0 and W_T represents the wealth at time 0 and T, respectively.

Remark 1 ***(Premanent Impact)***
Let us define the permanent impact function caused by a large trader by $f : \mathbb{R} \to \mathbb{R}$. Then, as [17, 22, 23] shows, the market excludes the dynamic arbitrage if the permanent impact function becomes

$$f(v) = kv, \tag{1.5}$$

for all $v \in \mathbb{R}$ for some $k \in \mathbb{R}_{++}$, that is, a linear function [20]. In addition, they theoretically demonstrate that *nonlinear* permanent impact can lead to no dynamic arbitrage.

According to this fact (as well as some empirical results), a lot of existing research including the one explained below analyzes an optimal execution strategy under a linear permanent impact model.

1.1.3 Structure of This Chapter

The rest of this chapter proceeds as follows. Section 1.3 introduces the so-called Almgren-Chriss (AC) model [2] in a discrete-time framework, a fundamental model for seminal theoretical papers on optimal execution problems. Section 1.4 then analyzes a continuous-time analog of AC model, which captures the significant role that the market impact and risk-averse feature of a large trader plays. In Sect. 1.5, we see the model examined by Ohnishi and Shimoshimizu [35], where the market impact caused by small traders as well as a large trader exists. The model also considers a transient feature of the market impact which Almgren and Chriss [2] does not incorporate. All of these models derive the optimal execution strategy explicitly so that these strategies can be used as a backtest from a practitioner's point of view. A bibliographic note (Sect. 1.6) and some appendices are placed at the end of this chapter.

1.2 Notations and Some Remarks

In this chapter, $\mathbb{Z}_{++}$ stands for the set of all positive integers, i.e., $\mathbb{Z}_{++} := \{1, 2, \ldots\}$. Likewise, we define $\mathbb{R}_+ := [0, \infty)$ and $\mathbb{R}_{++} := (0, \infty)$. $\mathbb{R}^d$ represents the set of d-dimensional real-valued vectors. Any vectors are defined as row vectors. $\mathbb{R}^{m\times n}$ denotes the set of all $m \times n$ real-valued matrices. For any $\mathbf{A} \in \mathbb{R}^{m\times n}$, we denote by $\mathbf{A}^\top$ the transpose of the matrix (or vector) $\mathbf{A}$. $\mathbb{E}[\cdot]$ denotes the expectation (operator), and $\mathbb{V}[\cdot]$ the variance, each defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. As for the differentiation of a function, for any twice-differentiable function $f : X \subset \mathbb{R} \to \mathbb{R}$, denoted by $f_t := f(t)$ for $t \in X$, $\dot{f}_t$ expresses the differentiated function of f evaluated at t and $\ddot{f}_t$ the twice-differentiated function. Also, for any vector-valued function