



Automated Market-Making under Inventory Risk: A Stochastic
Optimal Control Framework

Joshua Acton

Supervised by Professor Nick Whiteley
Level H/6
20 Credit Points

February 14, 2024

Declaration

I declare that the work contained herein is my own, unless explicitly stated otherwise.

Acknowledgement

I want to thank my supervisor Professor Nick Whiteley for his constant encouragement, insight and patience whenever I had questions. I would also like to thank my personal tutor Dr Raphael Clifford, and the entire Schools of Mathematics and Computer Science at the University of Bristol for putting together the BSc in Mathematics and Computer Science which I have had the privilege to study for the last three years.

I would also like to express my gratitude to my mum, Ms Karin Acton, for her unconditional love and support over the last 21 years, and finally to my girlfriend Viktoria Leins who has made my time at Bristol more special than I could have ever imagined.

To mum

Thank you for everything.

Abstract

This paper presents a review of the complex mathematical theory that attempts to model the dynamics of an automated market-maker under inventory risk in financial markets. We outline begin by outlining financial markets, their participants and their microstructure, before discussing the requisite mathematical tools from stochastic analysis, stochastic calculus and stochastic control. Next, we investigate the seminal 2008 paper 'High-Frequency Trading in a Limit Order Book' by Avellaneda and Stoikov (2008), which formalises the approach of a market-maker trading through limit orders and utilises the dynamic programming principle to solve for the market-maker's optimal bid and ask quotes. We then present a recent extension to this model which extends the process governing the underlying stock price from a simple Brownian Motion to the more standard Geometric Brownian Motion. Finally, we implement the model in Python and present it's empirical results when back-tested on real order book data from a cryptocurrency exchange.

Contents

1	Introduction and background	8
1.1	Introduction	8
1.2	Financial Markets	8
1.3	Measure Theory and Probability	10
1.4	Stochastic Processes	10
1.5	Stochastic Integration	10
1.6	Stochastic Differential Equations	10
2	Stochastic Optimal Control	11
2.1	Controlled Diffusion Processes	12
2.2	Dynamic Programming Principle	12
2.3	Hamilton-Jacobi-Bellman Equation	12
2.4	Verification Theorem	12
3	The Avellaneda-Stoikov Model	13
3.1	The Model	15
3.2	The Utility Function	15
3.3	The Optimising Agent with Finite Horizon	15
3.4	The Optimising Agent with Infinite Horizon	15
3.5	Modelling Limit Orders	15
3.6	Modelling Trading Intensity	15
3.7	The HJB	15
3.8	Asymptotic Expansion in q	15
3.9	Summary	15
4	Extension and Statistical Analysis of Orderbooks	16
4.1	Extension to Geometric Brownian Motion	16
4.2	Estimating the Frequency of Market Orders	16
4.3	Estimating the Size Distribution of Market Orders	16
4.4	Estimating the Temporary Price Impact of Large Market Orders	16
5	Numerical Analysis and Simulations	17
5.1	Replication of the Results of Avellaneda and Stoikov	17
5.2	Simulation of Extended Model for GBM	17
5.3	Estimation of Order Book Parameters for Real-World Data	17
5.4	Market Making in the Binance Order Book	17
6	Conclusion	18
A	“Appendix”	19
	Bibliography	20

List of Figures

1.1	An example orderbook	9
-----	--------------------------------	---

Chapter 1

Introduction and background

1.1 Introduction

This section aims to equip the reader with both the motivation and mathematical tools to begin to formalise problems in stochastic optimal control and mathematical finance, by first providing some background material on financial markets, their participants, and their structure, and then setting up the basic elements of measure-theoretic probability theory and stochastic processes which we will use to describe them. We will end with a discussion of the market-making problem and how we might go about formalising it.

1.2 Financial Markets

A market is simply some social structure that attempts to match those who want to sell a good or service to those who want to buy it. Modern financial markets, thanks to recent innovations such as the internet, satellite communication, and fibre-optic cables, are perhaps the most interconnected and widespread markets in human history.

Most people may have heard of the New York Stock Exchange, London Stock Exchange, or NASDAQ, but these are only one type of exchange for one type of financial asset, namely equity (part ownership of a corporate entity, individually called "stocks" or "shares"). There are also markets for commodities (oil, gas, industrial metals, precious metals, live cattle and more), bonds (pieces of government or corporate debt, where the holder receives fixed interest payments), currencies (including cryptocurrencies), and derivatives which are legal contracts whose value is some function of the price of a specified underlying asset. In total, on an average day, tens of trillions of US dollars worth of assets change hands.

All markets, whatever the good or service being exchanged, have something in common: Every seller needs a buyer, and every buyer needs a seller. But this raises some natural questions: What happens if no-one wants to sell (or buy)? What happens if the only prices at which people are willing to sell is far out of reach of those who want to buy? Enter the *dealer*: An entity who provides *liquidity* (ease of exchange) to market participants. A dealer does this by simultaneously offering to both buy and sell the particular asset, offering to buy at a slightly lower price than they offer to sell. This known as "making a market", and dealers in modern parlance may also be called "market-makers".

Dealers provide a crucial service in financial markets: By providing these quotes, they narrow the *spread* - the difference between the prices at which one can buy or sell an asset in the market. Hence, entities who may need to trade even in adverse market scenarios (such as companies needing to buy foreign currency to pay workers abroad, or oil producers seeking to hedge their production) know that they can reliably find a buyer or seller, regardless of the uncertainty of other market participants such as *speculators* -

Side	Price /\$	Volume
A	1.02	50
A	1.01	30
N/A	1.00	0
B	0.99	25
B	0.98	45

Figure 1.1: An example orderbook

those believe that a certain asset is under or overvalued, and trade it with the sole motive of making money buy selling it for more than they bought it or vice-versa.

Of course, there is no free lunch. Dealers do not provide this service to the market out of the goodness of their own hearts - they too have a profit motive. While the presence of dealers in the market narrows the spread, it does not eliminate it. The dealers aim is to be constantly selling the asset for a slightly higher price than it is buying it, and taking the spread as profit. In modern electronic markets with very high trading volumes, even in heavily traded assets with very narrow spreads, a spread of only 0.01\$ multiplied across millions or billions of trades can be very lucrative for the dealers who are fast enough.

So far we have discussed markets as an abstract concept, but in order to build a mathematical model of the dealer, we need to specify the framework under which the market operates. Most modern electronic exchanges, including those mentioned above, operate some version of a *limit orderbook* where participants can place two types of orders: a *limit order* or a *market order* depending on their needs. Limit orders specify a side (bid or ask, buying or selling), a quantity (how many units of the asset to buy/sell), and a price at which the order should be executed. These enter a queue of limit orders at the particular price level. Market orders specify the same information, but they do not enter a queue: The exchange operates a *matching engine* which takes incoming market orders and attempts to match them to existing limit orders, and if two orders match, they are executed and a trade occurs. For an example, consider the orderbook illustrated by If a market order is placed to sell 25 units, then the trade will occur at \$0.99, the dealer will buy and the placer of the market order will sell, and both orders will be removed from the market. However, suppose that a market order is placed to only sell 5 units. In this case, the orders will still be matched, the seller will sell 5 units for \$0.99 apiece but the limit order at \$0.99 will remain on the exchange, only now for 20 units instead of 25. Correspondingly, if the market order is placed for 100 units, the limit orders at both price levels will be "used up" and taken off the market, and the seller will only sell 70 units for an average price of $\frac{25 \times 0.99 + 45 \times 0.98}{70} = \$\frac{1377}{1400}$ per asset. If a market order is placed and there are no limit orders to match it against, the market order would not be executed at all and be voided.

Here we can see the key difference between market and limit orders in action: Limit orders guarantee price, but do not guarantee that all or any of the order will be filled. Market orders guarantee that as much of the order as possible will be filled, but they do not guarantee the price at which the trade will occur.

We can also observe that the market provides us with a way to estimate the true value of the asset. Classical economic theory dictates that in aggregate, market participants react quickly and rationally to new information about a particular asset, meaning that market prices reflect the consensus opinion of market participants about the value of traded assets. The spread exists because people would only want to sell for slightly more than something is worth, and buy it for slightly less. Hence, if you really want to buy an asset you have to pay a premium to "*cross the spread*" to acquire it. From this we can determine that the true price of the asset at a point in time lies somewhere in between

the maximum bid price and the minimum ask price for the asset at that time. The most common estimator in the literature is simply the average of these two values, but other estimators do exist such as the volume-weighted average price (VWAP) which takes into account the volume of the bids vs asks. For the rest of this paper we will use the midpoint price as our estimator for the "true" value of an asset.

The aim for the rest of this paper is to build up a model of how a dealer should behave to maximise their returns in the presence of uncertainty: namely, uncertainty about the path that the true value of the stock might take. In order to do this, we will need to make use of some basic results from measure/probability theory and stochastic processes, which we will summarise below. We will also briefly introduce some tools from stochastic calculus. Familiarity with standard results from a first-year undergraduate level course in real analysis is assumed.

1.3 Measure Theory and Probability

Measure theory, sigma algebras, filtrations, probability spaces, fubini/tonelli, moment generating function

1.4 Stochastic Processes

Markov chains, martingales, brownian motion, poisson processes

1.5 Stochastic Integration

Stochastic integral, Itos lemma

1.6 Stochastic Differential Equations

From PDE to SDE

Chapter 2

Stochastic Optimal Control

$$dX_s = b(X_s, \alpha_s)ds + \sigma(X_s, \alpha_s)dW_s$$

A strong solution to this SDE starting at time t is a progressively measurable process X such that for $s \leq t$:

$$X_s = X_t + \int_t^s b(X_u, \alpha_u)du + \int_t^s \sigma(X_u, \alpha_u)dW_u$$

and

$$\int_t^s |b(X_u, \alpha_u)|du + \int_t^s |\sigma(X_u, \alpha_u)|^2 du < \infty$$

a.s. We say that $\hat{\alpha}$ is an optimal control for a given initial condition $(t, x) \in [0, T) \times \mathbb{R}^n$ if

$$v(t, x) = J(t, x, \hat{\alpha})$$

where J is the gain function and v is the associated value function

$$v(t, x) = \sup_{\alpha \in \mathcal{A}(t, x)} J(t, x, \alpha)$$

and

$$J(t, x, \alpha) = \mathbb{E} \left[\int_t^T f(s, X_s^{t, x}, \alpha_s) ds + g(X_T^{t, x}) \right]$$

and $\mathcal{A}(t, x) \subseteq \mathcal{A}$ such that

$$\mathbb{E} \left[\int_t^T |f(s, X_s^{t, x}, \alpha_s)| ds \right] < \infty$$

where \mathcal{A} is the set of control processes such that

$$\mathbb{E} \left[\int_0^T |b(x, \alpha_t)|^2 + |\sigma(x, \alpha_t)|^2 dt \right] < \infty$$

and

$$f : [0, T] \times \mathbb{R}^n \times A \rightarrow \mathbb{R}$$

is a rolling reward function and

$$g : \mathbb{R}^n \rightarrow \mathbb{R}$$

is the terminal payoff function.

$$v(t, x) = \sup_{\alpha \in \mathcal{A}(t, x)} \mathbb{E} \left[\int_t^\theta f(s, X_s^{t, x}, \alpha_s) ds + v(\theta, X_\theta^{t, x}) \right]$$

for any $\theta \in \mathcal{T}_{t,T}$ where for $0 \leq t \leq T \leq \infty$ we denote the set of stopping times valued in $[t, T]$ by $\mathcal{T}_{t,T}$

$$-\frac{\partial v}{\partial t}(t, x) - H(t, x, D_x v(t, x), D_x^2 v(t, x)) = 0$$

where

$$H(t, x, p, M) = \sup_{a \in A} \left[b(x, a) \cdot p + \frac{1}{2} \text{tr}(\sigma \sigma'(x, a) M) + f(t, x, a) \right]$$

is the Hamiltonian of the associated control problem. We have the regular terminal condition of our PDE:

$$v(T, x) = g(x)$$

2.1 Controlled Diffusion Processes

2.2 Dynamic Programming Principle

2.3 Hamilton-Jacobi-Bellman Equation

2.4 Verification Theorem

Chapter 3

The Avellaneda-Stoikov Model

In this section we will walk through the methodology and theoretical results of Avellaneda and Stoikov [1]

- The dealer being modelled is one of many players in the market
- The ‘true’ price is given by the market mid-price
- The money-market pays no interest
- The agent has no opinion on drift or autocorrelation of the stock price
- Limit orders can be continuously updated at no cost
- The arrival frequency of market orders to the market is constant
- Limit orders are of fixed size 1

Assume the stock evolves according to a standard Wiener process with some variance σ^2 :

$$dS_u = \sigma dW_u$$

Consider an inactive trader who holds an inventory of q stocks until the terminal time T . The agent’s value function is

$$v(x, s, q, t) = \mathbb{E}_t \left(-e^{-\gamma(x+qS_T)} \right)$$

where x is the initial wealth in dollars, t is the present time and γ is a user-defined risk-aversion parameter.

The reservation price is the price that would make the agent indifferent between his current portfolio and his current portfolio plus one stock. So r^b can be determined from the relation

$$v(x - r^b(s, q, t), s, q + 1, t) = v(x, s, q, t)$$

and r^a solves

$$v(x + r^a(s, q, t), s, q - 1, t) = v(x, s, q, t).$$

We solve these to obtain

$$r^a(s, q, t) = s + (1 - 2q) \frac{\gamma \sigma^2 (T - t)}{2}$$

and

$$r^b(s, q, t) = s + (-1 - 2q) \frac{\gamma \sigma^2 (T - t)}{2}.$$

We define the “reserve” or “indifference” price to be the average of these two *given* that the agent currently holds q stocks:

$$r(s, q, t) = s - q\gamma\sigma^2(T - t)$$

The agent quotes the bid price p^b and the ask price p^a , and the current shape of the limit orderbook as well as the distances $\delta^b = s - p^b$ and $\delta^a = p^a - s$ determine the priority of execution when large market orders are placed. E.g. when a market order to buy Q shares arrives, the Q limit orders with the lowest ask prices will be lifted. Let p^Q be the price of the highest limit order executed in this trade. Then $\Delta p = p^Q - s$ is the temporary market impact of the trade of size Q . Then we have that if our $\delta^a < \Delta p$, our agents limit order will be executed. We assume that market orders will fill our limit orders at Poisson rates $\lambda^a(\delta^a)$ and $\lambda^b(\delta^b)$, decreasing functions of δ^a and δ^b resp. (further away from midpoint \rightarrow orders hit less often).

We now have stochastic wealth and inventory: Let N_t^b and N_t^a be Poisson processes with intensities λ^b and λ^a representing the amount of stocks bought/sold by the agent at time t . The inventory at time t is $q_t = N_t^b - N_t^a$ and the wealth process evolves according to

$$dX_t = p^a dN_t^a - p^b dN_t^b.$$

The objective of the agent who sets limit orders is

$$u(s, x, q, t) = \max_{\delta^a, \delta^b} \mathbb{E}_t \left[-e^{-\gamma(X_T + q_T S_T)} \right]$$

Assume constant frequency Λ of market orders. We want to determine some realistic functional forms for the relationship between the Poisson intensity λ and distance to mid-price δ . To do this we need information on: (i) the overall frequency of market orders, (ii) the distribution of their size, (iii) the temporary impact of a large market order. The distribution of size of market orders has been found to obey a power law:

$$f^Q(x) \propto x^{-1-\alpha} \quad (3.1)$$

for large x , with $\alpha \in [1.4, 1.6]$. Less consensus on size distribution. Some find change in price Δp after market order size Q given by

$$\Delta p \propto Q^\beta, \beta \in [0.5, 0.8] \quad (3.2)$$

while others find

$$\Delta p \propto \log(Q) \quad (3.3)$$

Using (1) and (3) we can derive the poisson intensity as

$$\lambda(\delta) = \frac{\Lambda}{\alpha} e^{-\alpha K \delta}$$

while (1) and (2) yield

$$\lambda(\delta) = B \delta^{-\frac{\alpha}{\beta}}.$$

[Need to figure out what B is]. Other methods exist i.e. integrating the density of the orderbook, potentially better since we only care abt short-term liquidity?

Ho and Stoll use the dynamic programming principle to show that a function u must solve the HJB:

$$\begin{aligned} u_t + \frac{1}{2} \sigma^2 u_{ss} + \max_{\delta^b} \lambda^b(\delta^b) [u(s, x - s + \delta^b, q + 1, t) - u(s, x, q, t)] \\ + \max_{\delta^a} \lambda^a(\delta^a) [u(s, x + s + \delta^a, q - 1, t) - u(s, x, q, t)] = 0, \\ u(s, x, q, T) = -e^{-\gamma(x + qs)} \end{aligned}$$

but due to our choice of exponential utility we can simplify the problem with the ansatz:

$$u(s, x, q, t) = -e^{-\gamma x} e^{-\gamma \theta(s, q, t)}$$

and by substitution we find the following equation for θ :

$$\begin{aligned} \theta_t + \frac{1}{2}\sigma^2\theta_{ss} - \frac{1}{2}\sigma^2\gamma\theta_{ss}^2 + \max_{\delta^b} \left[\frac{\lambda^b(\delta^b)}{\gamma} (1 - e^{\gamma(s-\delta^b-r^b)}) \right] \\ + \max_{\delta^a} \left[\frac{\lambda^a(\delta^a)}{\gamma} (1 - e^{-\gamma(s+\delta^a+r^a)}) \right] = 0, \\ \theta(s, q, T) = qs. \end{aligned}$$

By the definitions of the reserve bid and ask prices we obtain

$$r^b(s, q, t) = \theta(s, q + 1, t) - \theta(s, q, t)$$

and

$$r^a(s, q, t) = \theta(s, q, t) - \theta(s, q - 1, t)$$

and then through the following implicit relation we can obtain the optimal distances δ^b and δ^a :

$$s - r^b(s, q, t) = \delta^b - \frac{1}{\gamma} \log \left(1 - \gamma \frac{\lambda^b(\delta^b)}{\frac{\partial \lambda^b}{\partial \delta}(\delta^b)} \right)$$

and

$$r^a(s, q, t) - s = \delta^a - \frac{1}{\gamma} \log \left(1 - \gamma \frac{\lambda^a(\delta^a)}{\frac{\partial \lambda^a}{\partial \delta}(\delta^a)} \right).$$

3.1 The Model

3.2 The Utility Function

3.3 The Optimising Agent with Finite Horizon

3.4 The Optimising Agent with Infinite Horizon

3.5 Modelling Limit Orders

3.6 Modelling Trading Intensity

3.7 The HJB

3.8 Asymptotic Expansion in q

3.9 Summary

Chapter 4

Extension and Statistical Analysis of Orderbooks

4.1 Extension to Geometric Brownian Motion

Consider now an alternative model for the midprice of the security for which we wish to make a market:

$$dS_u = \sigma S_u dW_u$$

This defines the *Geometric Brownian Motion* (without drift), and is the canonical stochastic process used to model asset prices as in contrast with the standard Brownian Motion, this process is valued in \mathbb{R}^+

4.2 Estimating the Frequency of Market Orders

4.3 Estimating the Size Distribution of Market Orders

4.4 Estimating the Temporary Price Impact of Large Market Orders

Chapter 5

Numerical Analysis and Simulations

- 5.1 Replication of the Results of Avellaneda and Stoikov
- 5.2 Simulation of Extended Model for GBM
- 5.3 Estimation of Order Book Parameters for Real-World Data
- 5.4 Market Making in the Binance Order Book

Chapter 6

Conclusion

Appendix A

“Appendix”

Bibliography

- [1] Marco Avellaneda and Sasha Stoikov. “High-frequency trading in a limit order book”. In: *Quantitative Finance* 8.3 (2008), pp. 217–224. DOI: 10.1080/14697680701381228. eprint: <https://doi.org/10.1080/14697680701381228>. URL: <https://doi.org/10.1080/14697680701381228>.