MARKET MICROSTRUCTURE AND PRICE CONVERGENCE: A META-ANALYSIS

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ABSTRACT

The competitive equilibrium model is a universally accepted framework for determining market prices. It aligns with competitive market outcomes when its assumptions are fulfilled. These assumptions include the rationality of market participants, access to complete information, a large number of buyers and sellers, and the absence of transaction costs. This model predicts that markets will exhibit allocative efficiency, price convergence, and volume efficiency.

Initial empirical evidence in experimental economics shows how supply and demand forces establish the equilibrium price. Double Auction (DA) market experiments demonstrate efficient outcomes, even with fewer participants and market improvement rules. Subsequent variations relax market assumptions by replacing human traders with Zero Intelligence (ZI) agents in an agent-based model. These models achieve market efficiency through the Marshallian trading sequence. However, the introduction of an alternative (Randomized) trading sequence in this thesis reveals that market efficiency is sensitive to microstructure details governing market setup.

Rationality is introduced in an Agent-Based Model (ABM) populated with Zero Intelligence Plus (ZIP) agents to address shortcomings in achieving price convergence. Results of simulations with ZIP agents ensure that rationality, to some extent, is necessary for allocative and volume efficiency while achieving price convergence across different trading sequences.

This dissertation further evaluates the market efficiency of ZIP_H agents under various trading sequences and different demand and supply schedules, i.e., symmetric, asymmetric, and box-shaped schedules. Additionally, an empirical application of these theoretical results and implications regarding price formation is applied to the labour market, utilizing data from the HIES to assess the importance of market microstructure. The mechanism of price formation amid frictional (search and transaction) costs at varying minimum wage levels is evaluated. Additionally, the welfare impact of the minimum wage on market efficiency is investigated through alternative measures like the Matching Principle. Despite high market frictions, the results affirm that government involvement does not negatively impact employment levels but increases employment for specific market microstructure.

Keywords: Price formation, market efficiency, agent-based model, ZI agents, learning mechanism, market microstructure, price convergence, and competitive market.

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LIST OF ABBREVIATIONS

BGAN	Bayesian Game Against Nature
C&B	Cliff and Bruten
DA	Double Auction
G&S	Gode and Sunder
GP	Genetic Programming
HIES	Household Integrated Economic Survey
MS	Marshallian Sequence
ODA	Oral Double Auction
PP	Posted Prices
RS	Randomized Sequence
S&D	Supply and Demand
TP	Transaction Price
WTA	Willingness to Accept
WTP	Willingness to Pay
ZI	Zero-Intelligence
ZIP	Zero-Intelligence Plus
ZIP_H	Zero-Intelligence Plus with Human Learning Rules

CHAPTER 1

INTRODUCTION

The competitive equilibrium theory is central to modern economic theory. It illustrates how the market mechanism works to determine the price. In terms of the practicality of this theory, it is necessary to investigate the assumptions based on which this theory predicts market efficiency. These theoretical assumptions are questionable in real markets. Assumptions of competitive equilibrium theory imply that all market agents possess complete information, transactions without cost, and market forces aim to maximize surplus. Based on these assumptions, the economic theory predicts price convergence toward equilibrium and disregards issues raised when markets operate at disequilibrium or in the presence of any government involvement.

For more than a century, the idea of competitive equilibrium has remained persistent in economic theory. As per competitive economic theory, rational economic agents are utility maximizers, and their maximizing tendency leads the overall market toward equilibrium. This phenomenon of individual behavior causing a market equilibrium is supported by the most famous metaphor by Adam Smith (1976) as the 'invisible hand'. It is the bedrock of a free market economy as no kind of intervention is required for the market to work efficiently and it is best to let the markets freely work. This market efficiency is achieved when all the traders in the market gain maximum from trade. So, it is the only pursuit of rational economic agents that helps the market achieve efficiency and perfection.

Efficient markets are highly beneficial because they ensure that resources are allocated in the most productive way, leading to optimal economic outcomes. Additionally, efficient markets minimize transaction costs and reduce the likelihood of market manipulation, ensuring a fair playing field for all participants.

The assumption of the profit maximization tendency among rational economic agents, along with other assumptions, has been considered a contributing factor to market efficiency. So, the invisible hand theory works when economic agents are rational and markets are competitive. The theory of competitive market is criticized when the evidence from non-cooperative games comes in (Chamberlin, 1948; and Becker, 1962). The theory of invisible hands behind market efficiency has been just a theory until Becker (1962), and Smith (1962 and 1976) come up with empirical support for how the invisible hand makes the market efficient[1]. The convergence of transaction prices towards competitive equilibrium levels, as observed in experimental economics, highlights the self-correcting nature of efficient markets. This leads to overall market stability and improved economic welfare.

The predictions of competitive equilibrium theory get surprising support from these experiments as they are run under the framework of the Double Auction (DA) market. The supply and demand forces freely work in the competitive market while ensuring market efficiency. These experiments vindicate the invisible hand phenomenon as an engine of the market that controls the outcome. Initial results of experiments show that over time the market automatically achieves the outcome following the prediction of a competitive market (Plott, 1981). The invisible hand phenomenon works as the economic agents learn about the market environment and ultimately achieve close-to-competitive market efficiency. This market efficiency is reflected in the convergence of transaction prices between traders and the process is known as the market improvement rule. Prices

[1] Before Becker (1962) and Smith (1962), the experiment of Chamberlin (1948) showed that the traders are unable to have a maximum surplus from trades and the markets do not provide efficient results by themselves.

rise towards the competitive equilibrium level when they are below equilibrium, and prices fall when they are above equilibrium (Dhami, 2016, p. 268).

Initially, it has been thought that because of the rational behavior of market agents, as they gain experience and know about the market environment, they become successful in achieving the maximum possible profit. So, it is the learning process that is important in this process of price convergence, a decrease in surplus over trades, and an increase in the overall efficiency of the market. An artificial market environment is usually constructed to test the predictions of competitive market equilibrium in Experimental Economics (EE) under a controlled environment.

It is witnessed that human traders learn about the market environment and their rational choices, which evolve as they learn, cause an outcome in line with the predictions of the competitive market. The learning of human traders in the experiments is linked with their experience, information available, and type of market mechanism. Whereas, these experimental results are found robust to the number of traders (Smith, 1965), across different cultural backgrounds (Kachelmeier and Shehata, 1992), and in a market environment with extreme inequality (Smith, 2002; and Kimbrough and Symth, 2018).

Results of the S&D model have been robust in the initial experiments with various supply and demand environments and other market conditions. The robustness of these initial experiments raises concern regarding the necessity of learning of human traders (Becker, 1962). Skepticism is raised on the need for human learning in EE economics results and whether the market can achieve the same level of efficiency even if human learning is controlled (Dhami, 2016, p. 864). Along with the question of how important the learning in the DA market is, experimentalists also start digging into other assumptions of competitive market equilibrium i.e., full and cost-free information available to traders.

Controlling the learning process of traders has not been easy in experiments where humans always learn about their surroundings. To deal with the issue, Gode and Sunder (1993) introduce zero-intelligence (ZI) agents that are computer-generated artificial agents with no memory, controlled learning, and can be employed with a limited set of information available. The benefit of introducing these ZI agents is that the assumptions of rational behavior (depicted by human learning) can be tested in the S&D model. Like human experiments, the S&D model is analyzed for ZI agents in a simulated market. Testing of such a market environment in the presence of a ZI agent is known as Agent-Based Modeling (ABM).

An astonishing result emerges from the supply and demand by using ABM (Gode and Sunder, 1992, 1993, and 2003) with an artificially simulated market populated by ZI agents. These ZI agents have no memory, and a minimal level of rationality (enough only to avoid loss-making transactions) but are still able to obtain convergence toward the market equilibrium price level. These results of Gode and Sunder (GS hereafter) explain price convergence as the fundamental trait of the S&D model and verify that the market achieves maximum efficiency if left to work on its own. The market populated with agents having no learning mechanism achieves efficiency as predicted by economic theory. So, the S&D model shows that a market populated with no rationality and no learning mechanism can achieve efficiency even without following the assumptions of competitive market theory. The GS results suggest the non-necessity of rationality and learning at the individual level for the markets to be efficient. GS goes one step further by extracting the results from ZI populated market outcome, that the profit maximization assumption in neoclassical models is unnecessary for the markets to be efficient. This result is extracted from the results of GS as for the artificially created agents only the budget constraint is enough to earn the maximum surplus from trades. Meaning another basic assumption of a competitive market can be relaxed i.e., market participants must strive for profit maximization.

These results show that markets approximate rationality at the aggregate level even with no rationality at the individual level. So, in a competitive market, the invisible hand of Adam Smith works so well that even it doesn't need the traders to be rational. Supply and demand forces work by themselves in a way that leads the market automatically toward a competitive equilibrium outcome.

This outcome of the artificial market with ZI agents is counter-intuitive to the outcome of experimental models as the latter requires human intelligence for the market to achieve price convergence and surplus maximization. Here the question raised about the efficiency of markets – whether the invisible hand phenomenon in the competitive market is efficient enough that it doesn't require the market participants to be rational. While attempting to answer this question, a competitive market populated with ZI agents leads to an efficient level of output even with the same market conditions as in market experiments with human traders (Nicholas, 2022). These results are considered a breakthrough in the field of experimental economics.

These results coming from the application of experimental economics in ABM are phenomenal and found to be robust even with a very small number of traders across different types of market structures (like in human-populated markets). It is intriguing to explore the how S&D model provides such strong evidence while other models, especially in game theory, show the contrary results. The S&D model shows rationality is not even needed for the markets to be efficient.

The question to ponder here is whether the results of the S&D model with ZI-populated markets are due to market microstructure or the intrinsic property of the market. Market microstructure is the set of rules that constitute the market and how it shall operate. The results of auction markets are sensitive to the minor details of the market. Seemingly trivial changes in the rules regarding the market setup can lead to massive changes in the outcome. These details include the supply and demand function of the market, the information set available to the agents, transaction costs, and the rules that define how the trading takes place. These particulars of experiment or simulation are known as ‘microstructure’ (Biais, Glosten, and Spatt, 2005). It is imperative to understand how the market works and what rules the traders must follow. It is also important to know how they trade and what information is available to them. Additionally, understanding the impact of market frictions and whether government interventions cause inefficiency is crucial. Finally, it is essential to determine if these results align with the predictions of the supply and demand model. The testing of market microstructure is helpful to understand the phenomenon of how the market achieves efficiency, how the surplus of traders decreases over the trades, and how prices converge helps explain the price formation. It further tries to answer whether markets achieve efficiency without the traders being rational while having no learning mechanism.

This research explores the reasons for market efficiency shown in the ABM-based S&D model. The result of GS seems to be achieved only within some specific market settings as it is counter-intuitive that the markets achieve efficiency when agents do not possess rationality and do not attempt profit maximization. These early results, provided in the literature, are contrary to competitive economic theory as the S&D model is believed to work only under certain assumptions. For this purpose, the implication of the S&D model is evaluated through ABM while testing if the suggested results are due to market efficiency or because of any other underlying factors. The motivation for testing the results of S&D through ABM comes from the lack of intuition behind the earlier results of GS. This research first attempts to test the results of GS for different market microstructures to investigate if the S&D model still provides the results predicted by competitive market theory or not. After enforcing the significance of market microstructure, it is explained that the markets are not efficient by themselves but there exists a learning mechanism that the traders follow to maximize the profit. It is because of the learning of agents that the market achieves surplus efficiency[2] and prices converge to equilibrium.

While introducing rationality in agents, the next issue arises about the type of learning mechanism they follow. In the literature (Cliff and Bruten, 1997) the learning rules are not derived from how traders learn in the market but are assumed to maximize the market efficiency. The imposition of such learning rules does not provide a good understanding of the impact of rationality on market performance and its role in price formation. It does not provide any concrete evidence about the role of learning if we assume the learning rules by ourselves and pretend that the traders follow these rules in the market and the market achieves efficiency. The more appropriate way to do it is to take the learning rules from the actual experiments and then examine their impact on the market. Following this reason, we extracted the learning rules from the human-populated experiments and applied them in the ZI-populated market. The results of the competitive market in the presence of a learning mechanism enhance the market efficiency in terms of price convergence and surplus efficiency. Hence, the results show the importance of learning mechanisms for the supply and demand model to work, and the initial results of GS proved to be not satisfactory in explaining the market dynamics.

The S&D model initially explores market outcomes without intervention, positing that any market interference hampers efficiency and overall effectiveness. This study delves into a specific form

[2] Surplus efficiency means that each trader gets maximum profit from the trade and ultimately markets the surplus close to the theoretical competitive level of surplus.

of market friction, particularly minimum wage fixation, recognized as detrimental to the economy by impeding the free operation of supply and demand forces and hindering resource allocation.

Theoretical predictions suggest that setting a minimum wage above equilibrium reduces employment, a notion widely documented in economics textbooks. However, studies like Card and Kruger (1993) present conflicting empirical findings, indicating increased employment with a higher minimum wage in the restaurant market. This study contributes to the limited literature on the reasons behind these contradictions, specifically exploring the role of search and transaction costs for varying market microstructures using an ABM in the S&D model.

Another focus of this study is to examine the impact of market intervention on efficiency, challenging the perception that any government intervention always leads to societal welfare loss. Traditional measures of market efficiency, such as total surplus, often neglect the unemployed, while giving preference to a level of earnings over employment. Proposing a novel welfare measure – market employment level – the study argues that the societal impact and positive gains from employment outweigh the higher surplus with fewer employed individuals. By shifting focus from the pursuit of profits to achieving full employment, the study suggests increased overall welfare by emphasizing that resource utilization (full employment) is more crucial than surplus maximization with lower employment. In addition, this study also evaluates the market interventions by the government while taking the data for the labour market of Pakistan from the Household Integrated Economic Survey (HIES). The average wage rate data is used for this purpose. The results show that interventions are not always bad, but sometimes it leads to higher market efficiency, especially in the presence of market frictions.

So, it is imperative to examine the sensitivity of market efficiency with respect to market microstructure. If markets are not efficient or competitive then it raises to inefficiencies as markets may suffer from misallocation of resources, where capital is not directed towards the most productive uses. The presence of market inefficiencies leads to suboptimal economic outcomes and decreased overall welfare. Therefore, ensuring market efficiency and competitiveness is crucial and important to study.

The next section aims to explicitly provide the research objectives of the research.

1.1. Research Objectives

Keeping in view the above background, this research aims to test the assumption of a S&D model. The results of the S&D model with a ZI-populated market show no need for rationality for the markets to be efficient. This result is counter-intuitive and must be explored. For this purpose, the ZI-populated simulated market is examined for different microstructures to check how vigorous are the S&D model results. After exploring the impact of market microstructure, the role of learning in the market is assessed on how it supports market efficiency. For this reason, the learning rules based on human experience are developed and examine the S&D model outcome with an imposition of these learning rules. The S&D with different market microstructures may provide different results with and without the learning mechanism embedded in the ZI agents. In addition to investigating the role of market microstructure and the implication of human-based learning mechanism, the applicability of this research, the S&D model is applied in the labor market. In the context of the labor market, it is explored whether the relationship between minimum wage imposition and unemployment is sensitive to market microstructure.

More specifically, keeping in view above mentioned summarized theme, the research objectives of this research are as follows.

I. To explore why Zero Intelligence is not enough for the S&D model to lead toward market efficiency.
II. To examine if the efficiency of the S&D model is contingent to the market microstructure.
III. To investigate the role of rationality in achieving market efficiency.
IV. To extract the learning rules based on human experience in the experiments and explore if these rules help make markets more efficient for different microstructures in the S&D model.
V. To assess the impact of government intervention and market friction on the market efficiency across varying details of market microstructure in the labour market with the following sub-objectives.
   a. Assessing the impact of frictional (search and transaction) costs on employment levels in the labour market.
   b. Explaining the relationship between minimum wage and unemployment with and without market frictions.
   c. Investigating the welfare impact of minimum wage on labour market efficiency using alternative welfare measures.

1.2. Research Questions

The following are the research questions this research aims to answer.

I. If the efficiency of the market depends on the rationality of market participants?
II. How does the market microstructure cause to produce the same results as predicted by competitive market theory?
III. How effective is the learning behavior of traders to ensure market efficiency?
IV. What kind of learning behavior is closer to reality, and does it lead to a competitive equilibrium market?

V. To find out the impact of market frictions on the market efficiency in the labor market.

VI. To explore if the market frictions may lead to an increase in employment level in the presence of minimum wage laws.

VII. How sensitive is the welfare in the labor market to the market microstructure and how it can be enhanced?

1.3. Achieving the Research Objectives:

This research aims to assess the predictions of demand and supply theory in different market environments. This purpose is achieved in several stages.

First, we examined the market structure populated by ZI agents and then analyzed the factors that may cause the market to provide the predicted results while controlling the rationality, learning, and profit maximization behavior of agents. It is important to check the role of market microstructure in bringing the simulated market outcome closer to competitive market predictions. Different market microstructures are compared for this purpose, which helps to analyze whether changing the market microstructure also impacts the market outcome.

Second, once we find that market microstructure results from ZI-populated markets align with competitive market predictions, we take the next step. We replicate the ZI model by creating a new model with the same market framework. This new model can then be used to control the factors that may affect the market outcome. By controlling the trading sequences for the agents in the simulated market, our model shows that zero intelligence is not enough for the market to achieve overall efficiency at an aggregate level. Now, the reason for this result is the importance of the learning process of agents, without which price convergence, decreasing bid-ask spread, and aggregate surplus efficiency are not possible.

Third, after realizing the significance of learning in making the markets efficient, the question arises about which type of learning is more useful to be adopted by ZI agents. In this context, several learning models are already presented in the literature i.e., Zero-Intelligence Plus (ZIP) agents, Snipers, evolutionary learning, etc. But all these models are being built while focusing on the outcomes whether they match with competitive market outcomes or not. To address this issue, we have extracted the learning rules from actual human experiments and then applied these rules to ZI agents. It helps to imitate the actual human learning behavior in the simulated market instead of following the learning mechanism that is not derived from the real learning of market participants.

Fourth, then we replicate the model with ZI agents in ABM to find if we reach the same results as predicted by competitive market theory and achieved through ZI agents. As the purpose of the stimulated market with ZI agents is to imitate the human experiments, we tried to explore the differences between the market structure of ZI agents in simulated markets and human traders in experiments.

Lastly, to check how vigorous the results of our simulated learning ZI agents are, the learning model is applied to different market environments. For instance, varying supply and demand schedules are borrowed from literature, and then the learning of agents is evaluated in comparison to the actual learning of human traders in DA experiments. Symmetric and non-symmetric supply and demand schedules, box-shaped supply and demand, and schedules with different ranges of values and costs for sellers are used. It helps to also examine the robustness of our learning model in a simulated market with learning rules extracted from the behavior of real humans instead of assuming these rules.

1.4. Research Contribution

This research makes a substantial contribution to the understanding of market dynamics, particularly in assessing the assumptions of a competitive market through the introduction of Zero Intelligence (ZI)-populated Agent-Based Models (ABM). The research objectives and their corresponding contributions are outlined below:

I. Examination of Zero Intelligence Efficiency:

The research critically examines the inadequacy of Zero Intelligence for achieving market efficiency and price convergence towards equilibrium. By identifying the limitations of ZI, the study enriches our understanding of factors essential for market efficiency.

II. Market Efficiency Determinants:

The study investigates whether market efficiency results from inherent market dynamics predicted by competitive market equilibrium theory or if it is influenced by market microstructure. This exploration provides insights into the drivers of market efficiency, distinguishing between macro-level theory and micro-level structures.

III. Comparison with Human-Trader Populated Experiments:

The research explores the differences between a market framework populated with ZI agents and experiments involving human traders in a Double Auction setting. This comparative analysis offers valuable insights into the unique aspects of ZI-populated markets as opposed to those with human participation.

IV. Role of Learning Mechanisms and Rationality:

The study delves into the significance of learning mechanisms and rationality in simulated DA markets. By investigating these factors, the research contributes to a nuanced understanding of how learning and rational decision-making impact market dynamics.

V. Learning Model for ZI Agents:

The research builds a learning model for ZI agents and assesses its ability to replicate results obtained from experiments involving human traders. This contributes to the development of more sophisticated models for simulating market behavior, advancing our capability to mimic real-world market scenarios.

VI. Policy Implications with an application of the S&D model in the Labor Market:

The research provides policy implications by examining the importance of market microstructure in the labor market. Sub-objectives assess the impact of frictional costs on employment levels, explain the relationship between minimum wage and unemployment with and without market frictions, and investigate the welfare impact of minimum wage on labor market efficiency using alternative measures. These findings offer practical insights for policymakers addressing labor market challenges.

In summary, this thesis significantly advances our understanding of market dynamics. It addresses the limitations of Zero Intelligence and explores the determinants of market efficiency. The thesis compares ZI-populated markets with human-populated ones and assesses the role of learning mechanisms. It also provides valuable policy implications for the labor market.

CHAPTER 2

LITERATURE REVIEW

2.1. Market Theory in the History of Economic Thought

Competitive market theory is the main classical theory of economics with an intuitive explanation of market demand and supply introduced by Adam Smith in his famous book Wealth of Nations (1776). The concept of competition is found in early works of Austrians done on price theory (Menger, 1871 and von Wieser, 1893). The concept of marginal utility is central to the price theory and offers the theory of competitive market price formation. This neoclassical analysis of marginal utility assumes that traders choose quantities with respect to their marginal utility of the product while taking the prices given. As all the transactions have to be done at preset in such a market environment, the traders are left to only maximize their utility while having the choice to select the optimal quantities (Jevons, 1871). Jevon believes that all the traders in the market must have full or perfect information about the market so they know how each of them should buy or sell at the given price level. These predetermined price requirements of the market endorses that all the traders must go into the trade at the set price, called the 'Law of One Price'.

Walras (1874) takes this stand of theory even further by supporting the exogenous price setting in the market. It means traders have the choice only to select the optimal quantity level while taking the prices as announced in the market by the auctioneer (known as Walrasian Auctioneer)[3] [4]. But when the price is already set by the experimenter, then no need is there to find the equilibrium price, and it doesn't explain the price formation mechanism in the real market environments. In

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[3] Walras's Auctioneer mechanism is not easily found in practice. From 1919 util its abandonment in 2015, the London gold price is determined by using a procedure used in Walras tatonnement – but since its failure the Walras tatonnement is found nowhere else (Inoua and Smith, 2020).

[4] The working of Walrasian Auctioneer is well documented by Arrow and Debreau (1950) in their general equilibrium analysis.

other words, price formation theory limits the mechanism of how prices are determined in the market. Walras states that the price is exogenous, and all traders must trade at this one price. Traders make choices about the suitable quantity demanded or supplied. Walras's theory of exchange is originally based on the broker market, known as the Paris Bourse. In that market, all the traders can directly communicate with each other, and they can learn about the market. It's the broker who knows the aggregate demand and supply curves and matches buyers and sellers in the market at the market clearing price. So, market efficiency is achieved even without decentralized information.

Later, the mechanism of price formation in the market is explained by Alfred Marshall (1890) through the concept of price reservation theory. Walras and Marshall are often seen as opposing each other. However, according to Hicks (1934), their differences are mainly due to their interests. Walras is interested in exploring the general principles of the exchange market. In contrast, Marshall focuses on analytical instruments to explain the micro-details of the price formation mechanism. Walras's tatonnement considers the prices as independent variables and quantity demand and supply are dependent. For Marshall, it is the opposite. He considers price as the dependent variable and quantity as given. Marshall (1890) supports an old classical viewpoint of the market. This viewpoint involves traders in a multilateral process of higgling, bargaining, and trading with the most suitable trader. The modern price formation theories are built based on this old theory. Even the early market experiments use the discrete quantity space where the trade decision is implemented depending on the buyer's reservation price (or willingness to pay) and the seller's reservation cost (or willingness to accept) as illustrated by Marshal (1890).

2.2. Invisible Hand Metaphor and Price Theory

In the classical market, traders are involved in competition over buyer-buyer overbidding, seller-seller underselling, and buyer-seller haggling. This classical mechanism under a competitive market is motivated by Adam Smith in *Wealth of Nations*. Buyers and sellers come to the market with their revealable willingness to pay and willingness to sell in monetary terms. Collective market interaction between buyers and sellers helps form aggregate market demand and supply. It is through this process of aggregation of demand and supply at the market level that the price formation. This market-level demand and supply (aggregate demand and supply) and the price discovery at the aggregate level are not separatable in classical markets. It is only at the closure of a market that we can identify the quantity demanded and supplied in the market as a function of market price. Similarly, it is due to these market characteristics that convey Adam Smith's famous 'invisible hand' metaphor i.e., if the market is left free to work then its outcome is economically efficient as all traders will trade at the price level that helps them achieve maximum surplus level.

The Marshallian viewpoint used to explain the working of the invisible hand in the market comes from the adjustment of prices in relation to demand and supply in the market. As per Marshall, the traders on the left of equilibrium have more reservation prices than the cost of all sellers situated on the left side of market equilibrium[5]. Although all these traders positioned on the left of the equilibrium level (known as intra-marginal traders) will trade with each other, the traders situated on the right of equilibrium (known as extra-marginal traders) may also trade. This is due to the non-availability of full information. But over the trades and across the trading periods as the traders learn about the market the chances of extra-marginal traders decline. Smith's invisible hand

[5] Here another difference between the working of market mechanisms of Walras and Marshall is that in the Walrasian market, no trader is allowed to trade at a disequilibrium level of prices. Still, Marshall allows the traders to exchange even at a disequilibrium price level (Dhami, 2016, p. 863).

mechanism works here to automatically determine the pricing and make the traders learn about the market. It is because of this invisible hand mechanism (reflected through demand and supply in the market) that intra-marginal traders trade first and the market leads to efficiency as surplus from trades is extracted close to the prediction of competitive market theory.

2.3. Market Rationality as an Emergent Phenomenon

The invisible hand metaphor of Smith needs the traders to learn about the market. It is because of the rational choices the traders make that help to achieve an efficient market outcome. Here the rationality of traders is not what we consider traditionally as an 'absolute rationality' but an 'emergent rationality' (Inoua and Smith, 2020). From emergency rationality, it means that the traders keep learning the market as the trades happen and the WTP and WTA of others are revealed. An answer to the question, of how emergent rational behavior works in the market and how it leads to results of competitive market theory, is provided by Hayek (1945).

According to Hayek (1978), there is a scarce possibility of having a trade mechanism at an individual level that leads to market efficiency. The odds are very few that the traders in the market with little information at the individual level lead to a combined efficient outcome. However, it is an aggregate market mechanism that brings about rational order at the market level. This aggregate-level market process requires the sum of all knowledge that no single mind can possess and process. It is why the rationality at aggregate market level, coming from individual supply and demand functions, can coordinate the trade phenomenon to attain desired results (Basci and Yigittir, 2021). So, emergent rationality at the aggregate level is indispensable for an invisible hand to work instead of absolute rationality at the individual level. It appears that for the invisible hand to work, the learning of traders and their emerging rational behavior are inevitable in market mechanisms. Otherwise, the market may not lead to the desired results i.e., price convergence to equilibrium level.

2.4. Role of Market Microstructure

In literature, a large number of studies are devoted to exploring the importance of learning in the process of market trading that leads to price convergence. Starting from Chamberlin (1948) and Smith (1962), literature emphasized the microstructure of the Double Auction market and later Posted Prices (PP) by Plott (1986). The agenda of this research is to answer when the convergence to equilibrium takes place and when it does not. Along with the microeconomic theory (Varian, 2014), the lab experiments (Smith, 1982; William, 1981; Isaac and Plott, 1981; and Plott, Roy and Tong, 2013) and simulations (Gode and Sunder, 1993 and 2004; and Cliff and Bruten, 1997) provide necessary tools to answer this question. While answering the convergence question it is equally important to address the market microstructure that leads to price convergence and allocative efficiency. In literature, a few variations can be found in this respect. Reiter (1977), and Plott and Smith (1978) have supported the earlier results of DA while maneuvering the rules to publicly announce ask/bid prices. The results of DA show quick convergence to competitive equilibrium (Liang *et al.*, 2011; Jamal and Sunder, 1996; Parsons et al., 2006; Sherstyuk et al., 2020; Ladley, 2012; and Vytelingum, 2006).

These results depend on the specific details of the experiment or simulation. Few studies (have emphasized these details that may have a significant impact on achieving the desired results by setting up the market microstructure (Davis and Harrison, 1993). For the specific details, some studies focus on the characteristics of participants (Brewer *et al.,* 1993) while others (Attanasi, Centorrino, and Moscati, 2016; and List, 2004) on supply and demand functions. It is in the direct interest of this study to ponder what the details are being focused on in the literature and whether these details, which affect the market results, approximate the real markets.

In most of the studies (Easley and Ledyard, 1993; and Wilson, 1987) the first trade is held between the buyer with the highest reservation price – not necessarily the buyer of the highest value – and the seller of the lowest reservation price – not necessarily the lowest cost. However, these characteristics contradict the reality as participants do not have information regarding the reservation prices of other participants. Some studies (Davis and Holt, 1993; and Posada, Hernández, and Lopez-Paredes, 2008) involve more than one unit in trading where buyers are bound to buy higher-value units first and sellers are bound to sell lowest-cost units first. The study of Plott (1993) shows that such trading rules insert force to decline the price variation and cause price convergence. Gode and Sunder (1994) introduce another kind of individual characteristic where each seller is allocated an ask price randomly but between their cost and the upper limit. Similarly, each buyer is allocated a bid price randomly but that is between the value and the lower limit. As the cost of the seller increases the chances of getting a low ask price decrease and the opposite happens with the buyers. In these settings, the seller with the lowest cost and the buyer with the highest value are more likely to transact first. Such rules of microstructure are not found in real-world markets as no such restriction on ask and bid price is present.

2.5. Learning: A Key to Price Convergence

Friedman (1993) exhibits that one of the reasons for price convergence and allocative efficiency is the fixed values and costs to the buyers and sellers, respectively. In all the trading periods the cost and value remain constant which helps the participants in the experiment to automatically converge while improving their surplus. It is again in contrast to the reality where supply and demand are continuously changing. In this line, Brewer *et al.*, (2002) examine the convergence process in the continuously refreshed supply and demand and find that price convergence happens in human subjects but not with Zero Intelligence (ZI) agents[6]. These studies give rise to the question that if the values and costs are not the same and S&D functions keep changing in each period then what will happen to the convergence process? It is found that if buyers and sellers are resampled in each period even then price convergence and allocative efficiency can be attained (LiCalzi *et al.*, 2009). Their study keeps the S&D function constant over each period. Although resampling of buyers and sellers leads to price convergence under constant S&D functions it does not mirror the real market. Cliff and Bruten (1997) are of the view that even in the case of asymmetric supply and demand functions price convergence still happens when the S&D functions remain constant over periods. So, the literature shows various characteristics that affect convergence and allocative efficiency. Some studies focus on details while ignoring others. Mix results can be found regarding convergence depending on: the S&D functions (symmetric or asymmetric), changes in S&D function over periods, values and costs allocated to buyers and sellers; and if these values and costs are constant or change over time.

Along with the experiments, many studies focus on the convergence process in simulations by artificial Zero Intelligence (ZI) agents. The assumption of microeconomic theory exhibits that individuals are rational, and this property is considered a necessary condition for convergence (Varian, 2014). Earlier studies (Plott and Smith, 1978) express that price convergence is due to individual rationality, but later studies show otherwise (Gode and Sunder, 1993). Becker (1962) states that even irrational behavior may lead to convergence to competitive equilibrium (CE). This result is reinstated by Gode and Sunder (1993) while showing ZI agents can attain CE who possess

[6] Zero Intelligence agents are simulated objects used in agent-based modeling that act as machine traders and their performance is compared to human traders (Gode and Sunder, 1993).

no intelligence let alone rationality. These results of ZI have been reevaluated over time but mixed results are found.

A number of researchers (Gode and Sunder, 1993; Bosch-Domenech and Sunder, 2000; Preist and Tol, 1998; Gjerstad and Dickhaut, 1998; Shi et al., 2013; Huber *et al.*, 2007; and Brewer and Ratan, 2019) showed that convergence in case of ZI happens irrespective of S&D function and other details. On the other hand, some studies show that the price convergence of ZI agents is sensitive to specific details. For instance, Brewer et al., (2002) point out the convergence only in human subjects but not for ZI agents when the S&D is continuously refreshed. The same conclusion is reached by Jain and Varaiya (2006) who exhibit that when the behavior of corresponding agents (i.e. other buyers or sellers) becomes significant for decision making then convergence is less likely to happen.

The results of experimental economics show that convergence happens in human experiments when the invisible hand is at work (Smith, 1962 and 1982). However, studies involving simulations indicate that the invisible hand does not matter. Convergence can be attained even with irrational agents (Becker, 1962 and Gode and Sunder, 1993). These results of ABM contradict the foundations of microeconomic theory that lie on the assumption of rationality. These results are reinstated by Preist (1998), but it does not incorporate details regarding how the market microstructure helps the market to achieve price convergence and allocative efficiency.

Microeconomic theory suggests that the markets automatically converge to equilibrium if any shock hits (Dixon, 1990). This explanation of the working of markets under supply and demand forces is analyzed by Attanasi *et al.* (2010). They find that if any exogenous (supply or demand side) shock hits the market the supply and demand forces come into work and lead the price level to equilibrium. But in their study, the ZI agents are supposed to transact under the Marshallian sequence i.e., the high-value buyer and low-cost seller have a high likelihood to leave the market earlier.

Literature shows extensive research on different aspects of microstructure but most of these studies (Smith, 1982; Plott, 1993; and Gode and Sunder, 1994) follow the rules that approximate the Marshallian Path (MP). This MP has been the leading reason for convergence that is not highlighted in the literature. This research tries to answer the question if trading rules do not approximate the MP still the prices converge to the equilibrium or not. Only a few studies are summarized by Davis and Holt (1995) and Holt (1999) while later studies including Ladley (2012) and Dhami (2018) focus on the results but do not comprise the factors that cause these results.

It is further observed that the previous research focuses on one of the many factors that influence the outcomes of DA. For instance, Anufriev et al., (2013) emphasized on impact of information on the efficiency of markets, Chiarella, Iori, and Perello (2006) highlighted the role of transaction volume and price volatility on price convergence, Zhan and Friedman (2007) studied the impact of markup rules on allocative efficiency of the market, and Brewer *et al.,* (2002) investigated the effect of non-constant supply and demand schedules on market efficiency. Similarly, other studies focusing on ABM also dealt with only one factor at a time. These studies include Rouchier and Robin (2006), who studied the role of information asymmetry through simulation. Chen, Tai, and Tang (2009) focused on the impact of cognitive abilities. They compared the performance of humans with artificial traders.

Several studies can be found in the literature, taking one factor while examining its impact on market efficiency and price convergence for experiments and simulations across different microstructures. But no meta-analysis can be found that deals with all these factors as well as pair of these factors. This gap motivates us to study the convergence process, why convergence happens in some experiments but not in others, what are the factors at work behind the convergence process, and what influences the speed of convergence. The meta-analysis will help study several factors. It will examine what causes the transaction price to move towards a competitive equilibrium level. It will assess the impact on results if the market follows a microstructure other than the Marshallian sequence. The analysis will also explore the role of trader learning in achieving results predicted by competitive market theory. Finally, it will investigate whether learning is compulsory for simulated agents in agent-based models (ABM).

CHAPTER 3

Theoretical Framework

The efficiency of markets has been an area of discussion since the concept of competitive markets came into economic discourse. Theoretical and empirical efforts have been put into finding out the reasons and factors that contribute to market efficiency. Competitive markets are assumed to have an inbuilt phenomenon, called the invisible hand, that helps the markets to reach efficient resource allocation. However, there are some assumptions that the competitive market must fulfill otherwise it may not achieve efficiency. These assumptions are a large number of buyers and sellers in the market, full information available to every trader, and rational decision-making by the traders.

These sets of assumptions are considered necessary to be fulfilled for the markets to be efficient. Now how to test these assumptions has been a big question. Experimental economics suggest a way out by developing an artificial market with a controlled environment. It offers an opportunity to test the assumptions of the competitive market and examine what causes the market to be perfect. Is it an intrinsic nature of competitive markets or does something else cause efficiency? But first, it is necessary to describe the tool being used by the experimentalists for the last seven decades to debate and prove their arguments in favor or against the working of invisible hands in the free market.

3.1. Double Auction Market – Functioning and Efficacy

The DA markets can easily be found around us i.e., in the case of small markets like fruits and grain markets, and big markets like financial markets. In DA markets, like in other markets, all the traders/participants in the market are profit maximizers and they tend to make every decision aiming to extract as much surplus from trade as possible. The function of the DA market has many variants depending on how the market is arranged, what is the market structure and what is the trading mechanism.

Like in any market, in the DA market, on one side some buyers want to purchase the commodity while on the other side, sellers want to sell what they have produced. The first of these elements is the number of participants in the market. When the trade happens between two individuals i.e., one buyer and one seller, then it is not accounted as an auction but only an exchange. This exchange can be a barter exchange or may involve money. Then there come two other variants of auction dependent on how many participants there are in the market. If a seller uses an auction market to sell the produce and more than one buyer can join the auction, it is known as a 'forward auction'. In forward auction buyers compete to get the produce/commodity that a single producer wants to sell. Opposite to forward auction is the 'reverse auction' having more than one seller who comes to market to sell their products, and there is a single buyer. Buyers can then choose among the sellers with minimum selling price (Ganguly and Chakraborty, 2008).

Table 3.1: Variants of Markets as per Number of Participants

	Single Seller	**Multiple Sellers**
Single Buyer	Simple Exchange	Reverse Auction
Multiple Buyers	Forward Auction	Double Auction Posted Price Market

[Source: Author's own]

The last of these types is the double auction market i.e., a combination of both forward and reverse auctions. All the buyers and sellers in the market are active at the same time in competing and making the trade. In the field of experimental economics, it is the DA market whose outcome is closest to predictions of the competitive market.

In economics, the DA markets are used as one of the tools in the experimental market. It became famous and hundreds of DA experiments can be found in literature because of two reasons. First, the DA market experiments have similarities with major security markets around the world. As a result, the efficiency and practicality of DA experiments are more widely acknowledged. Second, the DA market is analyzed while testing different variants of it in various market settings to investigate how robust are its results in line with competitive market theory predictions.

In addition to the double auction market, another market structure is the posted price market where sellers set fixed prices for their goods or services. Buyers can either accept these prices and make a purchase or decline and walk away. There's typically no negotiation or bidding process. As compared to the double auction market, the posted price market has generally fixed prices and the market power is more inclined towards the sellers. The learning process is also slower for the posted price market as the fixed price cannot be changed frequently. It leads to barriers in the learning process and price convergence of the market. Literature shows that the price convergence and the market efficiency are not as fast and high as observed for the double auction market.

The next sections will elaborate on the utilization of DA experiments to analyze markets populated with different types of participants i.e., human traders and artificial agents.

3.2. How Does the DA Market Work?

The simulated market, first developed by G&S, produces quite surprising results while explaining the efficiency of markets with no learning mechanism, no rationality of agents at the individual level, and without information. As described earlier, to find out the reasons for market efficiency, decreasing bid-ask spread over the periods, and price convergence it is inevitable to examine how the market mechanism works (Dhami, 2016, p. 868). For this reason, here are the details of how experimental market mechanisms work illustrated in the human-populated market of Smith (1962) and the simulated ZI agents-populated market of Gode and Sunder (1993).

For this purpose, the allocation of information to the traders and market trading mechanism is important to understand. Availability of information is important as it helps the traders to make rational choices as per competitive market theory. Similarly, trading rules are set in the market to set the rules about how traders trade with each other.

3.3. Importance of Market Microstructure

The double auction market gained importance over the years due to its ability to provide the results predicted by competitive market theory. Different methods are used to check the robustness of the results initially obtained by Smith (1962 and 1965). One of these tools is offered by experimental economics (EE) known as a market experiment to test the propositions of competitive market theory in a controlled environment. The other tool is the artificial market, known as an agent-based model (ABM), used to control the variables that the experimenter is not able to control even in a controlled market environment.

The results that are obtained by any of these methods are sensitive to the minor details of the market. Seemingly trivial changes in the rules regarding the market setup can lead to massive changes in the outcome. These details include the supply and demand function of the market, the information set available to the agents, transaction costs, and the rules that define how the trading takes place. These particulars of experiment or simulation are known as ‘microstructure’ (Biais, Glosten and Spatt, 2005). Microeconomic theory pays a lesser amount of attention to micro-structure while suggesting it does not matter. In contrast to microeconomic theory, the microstructure has huge importance in EE and ABM. The next sections will explain more about the details of market microstructure. This includes how values and costs are allocated to traders. It will also cover how supply and demand functions of the market are set. Additionally, the sections will discuss how traders learn and gain experience. Finally, they will outline the trading rules that traders follow.

3.3.1. Allocation of Values and Costs

Before the start of the experiment, all the traders are informed about the good that is to be traded and has properties that are homogeneous for all traders. Then traders are divided into two categories: buyers and sellers. Both types of traders must trade while facing some constraint or it's the same as maximizing the profit/surplus while facing a budget constraint. The budget constraint faced by the traders is different depending on the type of traders. For buyers, redemption values are given by the experimenter and these redemption values are allocated to all buyers before the start of the experiment. The redemption values are the upper constraint faced by buyers in terms of shouting the maximum price at which the buyer is willing to buy. This maximum price at which a buyer can buy the good is called the 'Bid Price'. The redemption value is the maximum value of goods that buyers want to buy in the market. Now buyers want to buy the good at the lowest price possible assuming he/she seeks profit maximization. The higher the difference between the bid price of the buyer and the respective redemption value, the higher will be the surplus of that buyer. So, the traders on one side of the market (buyers) got the redemption values and made the shouts to fulfill their demand and make a profit. Buyers always want to buy at the minimum possible price to maximize their surplus but if they shout a very low bid price then no seller will be willing to sell their produce to them. Buyers must shout the bid price carefully keeping in view their redemption value (as they cannot bid more than it) and the market supply (as buyers cannot shout a very low bid price which may not be acceptable to any seller).

On the other side of the market, there are sellers. Like buyers, sellers face constraints. They ought to maximize their surplus while confronting the constraint. Each of the sellers is allocated the cost of goods that is incurred in making it and bringing it to the marketplace. This cost is the minimum value they can charge for their produce. The higher the value they can charge for the product to be sold, the higher can be their surplus. Sellers must maximize the surplus while covering the cost as they cannot charge a price lower than the cost or are not allowed to trade at a loss. It is just opposite to the constraint of buyers as they cannot pay the price higher the value of the good. The higher the price the seller shouts at which they want to sell their produce, the higher can be the surplus. But if they ask for a very high price then they may end up selling nothing because buyers will always go for a seller with a lower price assuming the good has the same quality.

3.3.2. Market Demand and Supply

Once the buyers and sellers are allocated redemption values and costs, they have the first set of information that helps them to know their range to select the shout price. The set of information that is helpful to traders is the shout prices of other traders as their acceptance/rejections help to get an idea about market demand and supply. Market demand is nothing but the sum of all the redemption values of all the buyers in the market. For the market demand to be negatively sloped, the redemption values of all the buyers are arranged in descending order. The same is for the market supply as it is the aggregate cost of all the sellers participating in the market. If the costs of all the sellers in the market are arranged in ascending order and then drawn on a graph it will be a positively sloped line.

Once the market demand and supply are known (as it comes from the allocation of redemption values to buyers and costs to sellers) then the market equilibrium can be drawn[7] i.e., the intersection of market supply and demand curves on the graphs. From these allocated redemption values to buyers and costs to sellers, the experimenter can know about the theoretical equilibrium price. At this theoretical equilibrium price, the market offers to achieve a maximum market surplus. This market surplus is the sum of all the individual surpluses gained by all traders in the market. At the theoretical equilibrium price, the maximum theoretical surplus can be achieved as predicted by competitive market theory.

The number of goods that can be traded at this theoretical equilibrium price is known as competitive equilibrium quantity. On the other side, there is a price level at the point of intersection of market demand and supply known as competitive equilibrium price. These competitive levels of quantity and price ensure maximum surplus is extracted from the trades.

Now the question arises whether there is also a possibility that the number of trades can be equal or even more than the competitive quantity level at the equilibrium price level but still the surplus is lower than the competitive market surplus. To understand it, it is more helpful to take help from an example. Let's suppose that the buyers are allocated redemption values and sellers with the costs as given in Table 1 of the Appendix[8]. There are a total of 22 traders, equally divided between buyers and sellers. Buyers (sellers) are arranged by ordering their redemption values (costs) in descending (ascending) order.

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[7] This is only possible when the demand and supply curves are well-defined and cross each other. Otherwise, in case these curves do not intersect, the equilibrium cannot be defined.

[8] The market structure (redemption values for buyers and costs for sellers is borrowed from Cliff and Bruten (1997). The reason for taking this market structure is that the market demand and supply generated from these information sets is symmetric meaning that demand and supply curves are just opposite of each other. This simple market structure seems more helpful in understanding the market environment.

By using the redemption value allocated to buyers and the costs allocated to sellers, the market demand and supply can be drawn (as shown in the figure below). The market demand and supply graph show that the demand curve comes from drawing the redemption values and the supply curve is from the costs allocated to each of the sellers. The point at which these two curves intersect is called market equilibrium. Market equilibrium is the combination of the equilibrium level of prices and equilibrium quantity.

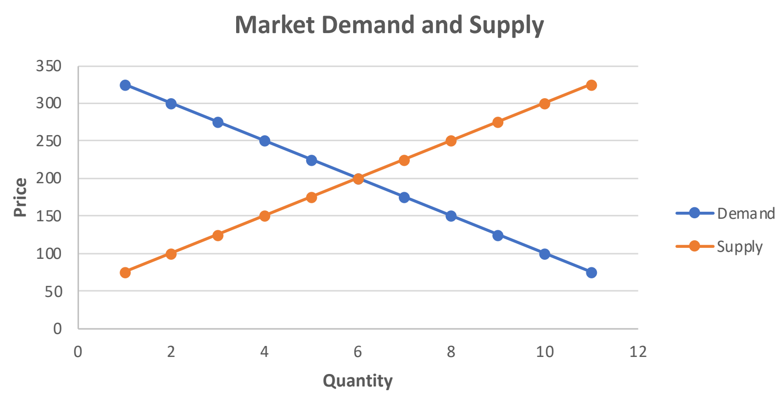

Figure 3.1: Market Equilibrium Price and Quantity [Source: Author's own]

In the graph above, the equilibrium level of price is 200 and at this price level, six units of goods can be traded. As per the competitive market theory, six buyers and six sellers can successfully make the trade. To achieve the results in line with the competitive market theory, the buyer with maximum redemption value (buyer with ID 1 and redemption value 375) shall trade with the seller having minimum cost (seller with ID 12 and cost 75). Similarly, the buyer with the second highest redemption value (buyer with ID 2 and redemption value 300) shall trade with the seller having the second lowest cost (seller with ID 13 and cost 100). This process keeps going until there remains no buyer in the market who has a value higher than the cost of any of the sellers. The theoretical arrangement of buyers and sellers in the market following their values and costs helps to know about the maximum level of surplus that can be extracted by the traders. When the trades happen ideally, as illustrated by competitive market theory, the trader at the rightest side of the graph is going to make the highest surplus in the market. This sequence of trading is a well-known Marshallian trading sequence that ensures maximum surplus, decreasing bid-ask spread over the trades, and price convergence towards equilibrium.

The reason for the high level of surplus is the utmost possible difference between their constraints and the shout prices. For instance, buyer 1 can make the shout price any amount less than the allocated value (i.e., 375), and seller 12 can shout any price higher than its cost (i.e., 75). If both traders agree to trade at the middle price, for instance, then both can make an equal amount of surplus. These first traders (or buyers and sellers positioned at the rightest side of the market demand and supply) are going to make maximum profit in total regardless of the trading price[9]. If the Marshallian trading sequence is followed in the market, then the aggregate market surplus will be maximum. If look at the pattern of how the buyers and sellers trade, the surplus from trade is going to drop with each passing trade. It is because in the first trade (that happens between a buyer of the highest value and seller of the lowest cost) the sum of their surplus will be highest. Then in the second trade (that occurs between the buyer of the second highest value and seller of the second lowest cost) the total surplus of these traders will be the second highest. In this way, the surplus will keep decreasing over the trade.

A decrease in the surplus of traders over the trades in the market ensures that the range of possible transaction prices is also decreasing. It is because, for the buyer with the highest redemption value and the seller with the lowest cost, the transaction price can be set in between this range depending on their shout prices. For the second highest redemption value buyer and second highest cost seller,

[9] For example, if both, the buyer, and seller at the rightest side of market demand and supply, trade at any price their total surplus (i.e., a surplus of the buyer plus the surplus of a seller) will be the maximum as compared to trades between all the combinations of buyers and sellers.

this range of shout prices decreases as compared to buyer 1 and seller 12. Due to this decrease in the range of possible shout prices, the range of possible transaction prices also declines. It is because the transaction price is equal to the shout price of the trader who shouts first, and the other trader decides to accept/reject the opportunity to trade. Now this decrease in the range of transaction prices ensures that over the trades, the transaction price will move closer to the theoretical competitive market equilibrium price level. This phenomenon is known as the price convergence of actual transaction prices towards theoretical market prices. It is also one of the predictions of competitive market theory that over the trades the transaction price convergence towards an equilibrium price.

If the trades are ensured in any way to happen as illustrated in the graph above, then it means that all the traders positioned on the right side of the equilibrium will be able to trade. The traders on the right side of the equilibrium point mean that buyers who have redemption values equal to or more than 200 and all the sellers who have costs equal to or less than 200. In total 12 traders (six buyers and six sellers) out of 22 traders are eligible to trade in this market environment. All the traders who are eligible to trade in the market are known as intra-marginal traders[10]. Opposite of it are the extra-marginal traders i.e., traders placed on the right of equilibrium price level. Theoretically, all the intra-marginal traders are eligible for trade as their trade with each other produces the maximum market surplus and hence makes the market efficient.

The total number of trades that happen between all the intra-marginal traders states the equilibrium number of quantity traded. In the example above, as there are six buyers and six sellers on the right

[10] The intra-marginal traders can further be divided into intra-marginal buyers (having redemption values equal to or more than the equilibrium price) and intra-marginal sellers (those who have costs equal to or less than the equilibrium price level). As per the Marshallian trading sequence, only the intra-marginal traders should be allowed to trade to achieve market efficiency.

side of the equilibrium a total of six trades can happen and this will be the competitive equilibrium quantity in the market. Equilibrium quantity may change depending on the market environment. For some markets the number of intra- and extra-marginal traders are equal, and, in that case, the total number of competitive equilibrium quantity is equal to the total of non-potential trades. But these conditions can be altered.

Such a market demand and supply function is known as a symmetric demand and supply. In this system, the number of intra- and extra-marginal traders is equal. The difference between the redemption values of buyers and the costs of sellers decreases with the same proportion. This process continues until equilibrium is achieved. The opposite of it is the non-symmetric demand and supply function. In this, the number of intra- and extra-marginal traders is not equal. One of the most famous types of non-symmetric market demand and supply includes box-shaped demand and supply. In this type, the difference between redemption values from the equilibrium price and the difference costs from the competitive equilibrium price is not the same. The more complex type of non-symmetric demand and supply function have the same slope of both curves i.e., either both demand and supply curves are positive or negative. But this type of market is quite rare to find.

The discussion above explains several aspects of the market environment. It details how redemption values are allocated to buyers and costs to sellers. It describes how traders shout prices to make a successful trade. It also covers how traders earn surplus and how their surplus decreases over trades. The discussion includes how to measure the theoretical competitive equilibrium market price and how transaction prices converge towards this equilibrium price level. Finally, it explains how to calculate the competitive equilibrium quantity that should be traded in the market.

3.3.3. Trading Period

The double auction market has different trading intervals, usually known as trading periods in experiments. The market may have one or more than one trading period. Each trading period has its own set of information available to the traders. This set of information may remain the same or may vary over the periods depending upon the discretion of the experimentalist. For instance, the market of Chamberlin (1948) has only one trading period and the experiment ends on the completion of that one trading period. Whereas the experiments of Smith (1962 and 1965) have more trading periods i.e., five trading periods in one experiment. Similarly, Isaac and Plott (1981) have a total of eight periods in their market experiment. The number of trading periods can be changed as per the interest and area of focus of the experimenter.

The basic purpose of increasing the number of periods in a single experiment is to investigate how the pattern of transaction prices, trade surplus, and trade quantities evolve over the periods. The reason for not relying on one period is that in the initial periods, the traders are not aware of the market environment, and they need time and experience to learn about the market. Once they learn about the market environment or absorb the information then they are in a better position to make more competitive shouts. This behavior of traders to learn and experience over the periods to be able to make more competitive shouts can only be achieved when they are allowed to trade in more than one period but with the same market environment.

Experience that traders get over the periods and their learning about the market helps them to avoid mistakes i.e., to shout a price that is not only acceptable to the other side of the market but also maximizes their surplus. This process of getting experience is necessary for human traders to make rational decisions in the market. It is also one of the assumptions of competitive market theory that all the market agents are rational. Having more than one trading period ensures that traders get enough time to gain experience and learn about the market to make the best decision for themselves.

For better learning over the trading periods, in almost all the experiments the experimental environment is kept the same, or no changes are made to it. What it means is the redemption values of the buyers and the costs of sellers are constant over the periods. In other words, the demand and supply schedules remain constant over the trading periods. Keeping the demand and supply constant does not mean that the experimenter allocated different redemption values and costs across different sellers randomly. It can be one of the market environments. However, in most experiments, especially early ones that support the results of competitive market theory, traders are allocated values or costs at the start of the experiment. These values or costs remain constant over the periods (Smith, 1965). However, this allocation of values and costs to traders may change over the periods as the experimenter can randomly select the buyers and sellers and allocate values and costs. This randomness of values and costs across the traders over the trading periods is only useful for human-populated markets but not in artificial markets populated with ZI agents. It is because only humans can learn about their environment, but ZI agents only follow the rules of the game.

Another way of changing the supply and demand function over the trading periods is to replace the old redemption values and costs with a set of entirely new values and costs. It will constantly change the supply and demand functions over the periods but limit their ability to learn about the market.

3.4. DA Framework with Human Traders

Experimental economics proposes a market with a controlled environment and specified microstructure, called Double Auction, that helps to answer the question about how the market achieves theoretically predicted results. Chamberlin (1948) was the first to test the predictions of a competitive market while controlling its assumptions. By imitating a real market, populated with human agents, he concludes that the oral double auction market leads to results a bit closer to the theoretical predictions of competitive market theory. Chamberlin runs the experiments while controlling the assumptions of a competitive market i.e., a large number of buyers and sellers, and rational traders.

One of the shortcomings, highlighted later, in Chamberlin's (1948) experiments is that it does not allow the full information available in the market. It was due to how the market is organized by Chamberlin (1948). In his experiment, the traders must go separately from each other and make a trade. The information about the bid price shouted by buyers and the ask price shouted by the seller was not available to everyone. It was due to this reason that the market of Chamberlin was not able to achieve the efficiency promised by competitive market theory. Later, this issue is reconsidered by Smith (1962) by trying to fulfill the competitive market theory assumption. It is because unless the assumption of competitive markets is not fulfilled the predicted results may not be achieved. These results were then supported by Smith (1965) and Backer (1962). The market structure used in the classroom experiments of Chamberlin (1948) and Smith (1962) is a bit different in detail although feels to be the same.

These details of market structure help explain the market characteristics of the Chamberlin experiment. One of these characteristics is that the buyers and sellers keep haggling and bargaining in the marketplace until they reach a contract, or the time ends. Once the contract is made, the transaction price is recorded and announced on the market. It shows that one trader (either buyer or seller) is engaged with only one counterpart until they decide to go into a contract or move to other traders in case, they couldn't reach any contract. All the traders are active at one point in time to trade with anyone. It means the chances of trade after bargaining with all the traders are very low in this market environment.

The market structure of Chamberlin makes the trade likely to execute at the earliest possible option. The reason for this argument is that the trader is unlikely to know about the bid and ask shouts of other participants but only aware of a trader with whom the interaction is made. In Chamberlin's experiment, the number of traders is quite small on both the supply and demand sides. There is also a time constraint to make the trade within a given period. As a result, traders look for any opportunity to make a significant profit. Such market structure encourages the traders to make the trades in haste while not having full information about the market.

The assumption of a competitive market regarding the availability of full information to all traders is not fulfilled in this market structure. As all the buyers and sellers in the market are free to trade with anyone in a room, they must physically go to know about other traders' bid/ask prices. Traders when feel that the trade is profitable then the transaction happens. However, the bid price of successful buyers and the ask price of successful sellers are limited to themselves. Once the buyer and seller agree to trade then only the transaction price is communicated publicly. This is why other traders are not aware of shout prices that reflect information about the success rate. They also do not know about previous shouts. As a result, they cannot make more appropriate shout prices where they think the trade is more likely. Publicly announced transaction prices only provide very limited information unlike bid and ask shouts. It is due to this reason that Chamberlin's market is not able to achieve very high efficiency as predicted by competitive market theory.

The second characteristic of these initial experiments is that the market is open only once for buyers and sellers with constant values and costs respectively. When the market is open for only one period and traders do not get a chance to improve the bid-ask shouts then the learning of traders is not doable. The proposition of rational decision-making depends on how fast the traders learn about the market and make rational decisions that help them to extract maximum surplus. But this barrier to learning of traders also limits the rational decisions to gain maximum surplus. When the traders are not able to gain the maximum possible surplus, the aggregate market surplus also declines. It makes the market less competitive and DA experiments with such a market structure, i.e., having one period in the experiment, do not lead to the results predicted by competitive market theory.

These assumptions of traders' rationality and availability of full information are not fulfilled in this market structure. The market structure of Chamberlin's experiment with human traders is illustrated in the figure below. The market structure comprises four simple steps. Here not only the steps of the trading mechanism are explained but the constraints in the trading mechanism of Chamberlin are also examined.

In the first step, redemption values are allocated to all the buyers in the market. However, on the other side of the market, the sellers are given the cost. These redemption values and costs determine the market demand and supply functions that are symmetric. These redemption values for buyers and costs for sellers do not come from any theory but are assumed and specified by the experimenter. Here, the shout prices of all traders may depend on how the supply and demand functions are structured. For instance, if the range of all redemption values is very high then it may have a different impact on the learning of traders as compared to the redemption values with low range (as in the case of Chamberlin). The same is the case for the seller. Similarly, if the starting point of redemption values and costs is very high but the range is low then traders may end up with a smaller number of trades as they seek a high profit margin. But this area regarding how these ranges and starting points impact the shout prices, transaction prices, and price convergence remains unexplored.

Once all the traders get to know about their role and allocated values or costs then they are free to haggle over to find a suitable partner to do trade. Buyers are looking for a seller who is selling at a low price so they can earn the maximum possible profit (their profit is the difference between their redemption value and the transaction price). On the other side, the sellers are trying to find a buyer who is willing to buy their produce at the maximum possible rate so they can gain a high profit (the profit for the seller is the difference between their cost and the transaction price). This is like of tug of war where a buyer wants to pay as minimum as possible, and a seller wants to sell the produce at the highest possible price.

Depending on their allocated values and costs both parties (buyers and sellers respectively) make up their minds about the price they shall trade (buy or sell). In all types of market structures, redemption values allocated to buyers and the costs allocated to sellers are private information and no one knows about it except the trader to whom it is allocated in the first step. But then there is another difficulty traders must face. Traders do not know about the shout price of others at which they want to buy or sell the product. It is due to this reason; that all the traders have to go physically to each other to get to know about the price at which they want to trade. They are also allowed to negotiate with one another. While going through this process, another constraint the traders face is the time constraint. All the traders are asked to close their trade within the allowed time by the experimenter. Once this time has passed, then no trader will be able to make the trade, and they will end up making no profits. So, the traders are facing multiple constraints in this market they have to consider while trying to make the trade. This haggling over of traders limits the possibility of getting to know the shout prices of all the counterparts. It is because of the time limit set to make trade in the market and after that period no trader will be able to make trade. Time for the trading period puts pressure on the trades to make the trade as soon as possible otherwise the trader may end up with no trade at all. To make any positive profit the traders must trade. Owing to time constraints and the non-availability of full information about the shout prices of all traders, in this trading mechanism, it is nearly impossible to make a rational decision. The trading environment proposed by Chamberlin provides a market outcome that is not the same as the one predicted by competitive market theory.

In the second step of the trading mechanism, the traders learn about the shout prices of their counterparts. Now they can decide whether to go into the trade if they can make the expected profit or they may also decide to go to any other counterpart in search of a better opportunity to make trade. Here the first order condition that the traders have to follow is to make a profitable trade i.e., the buyer (seller) shall trade at a price lower (higher) than their redemption value (cost). In the process of haggling over if the trader finds a potential buyer/seller to make a profitable trade then they go into the transaction otherwise the traders will move to other traders as a repetition of step 2. The transaction price is decided among the traders, and it is recorded and announced in the market at the end of the trading period.

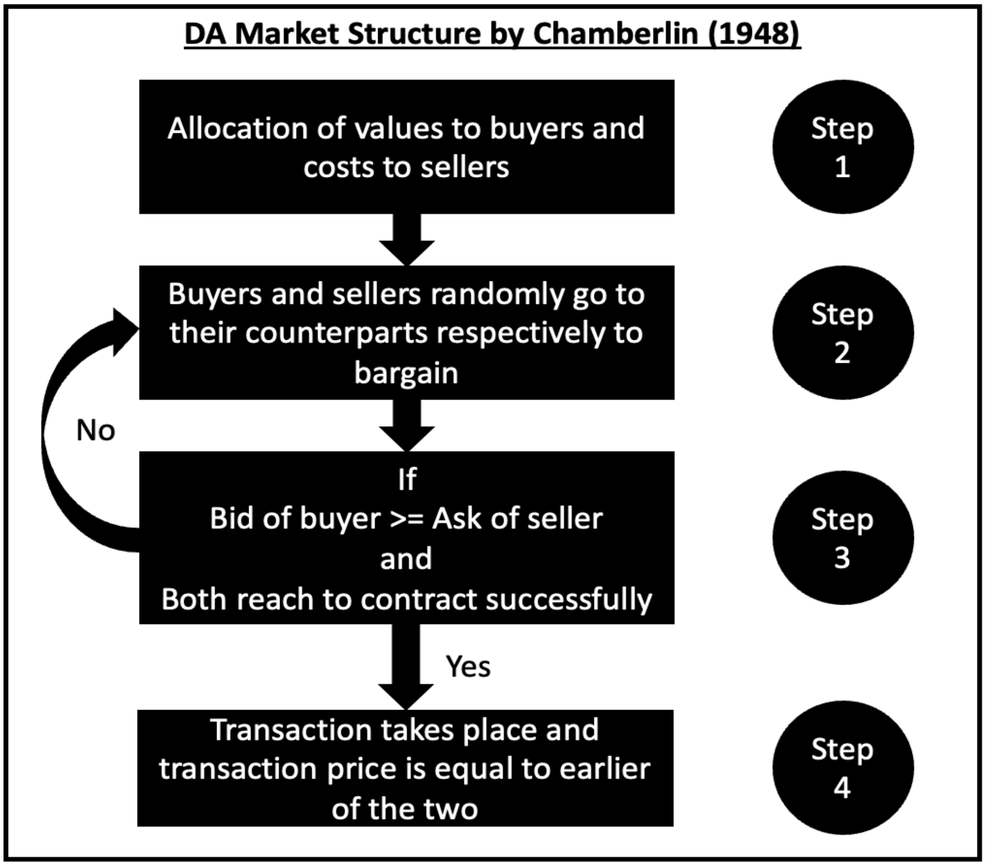

Figure 3.2: ODA Market Structure by Chamberlin (1948)

By using this simple market structure of ODA, Chamberlin is successful in achieving market efficiency close to the competitive market predictions[11]. These results of Chamberlin are achieved while not following all the assumptions of the competitive market, it is later thought that the market efficiency can be improved further. The used market structure has not fulfilled the assumptions and is also structured in a way that makes it possible to achieve 90 percent efficiency. In this experiment, the demand and supply schedules used are symmetric to each other. The actual number of trades with supply and demand schedules is higher than the theoretically predicted number of trades. However, the surplus from trade has not been declining for this market structure. In terms

[11] In terms of trade volume, Chamberlin (1948) achieved efficiency even more than the theoretically predicted volume. Whereas the average price level of the trades across all the experiments has been higher than the competitive equilibrium and no convergence is observed.

of market efficiency, the results of Chamberlin are not very close but are still considered in line with theoretical predictions of the competitive market. The surplus from trade does not have a declining trend over the trades which is not as predicted by competitive theory.

These initial results of the DA market experiment with some support to competitive market theory motivate researchers to explore more by varying the market microstructure. As explained, the results of Chamberlin (1948), although they are not closer to competitive market predictions, still provide the way forward to explore the viability of the S&D assumptions. For this purpose, the assumptions that are not kept on in the early experiment of Chamberlin are attempted to be considered. This is what Smith tries to achieve in his later experiments (Smith 1962 and 1965). After Chamberlin, Smith (1962) tries to explore if DA experiments with some differentiating characteristics can lead to the results as predicted by competitive market theory. Chamberlin's experiment does not fulfill the assumption of full information to all the traders in the market. In the market structure proposed by Chamberlin (1948), the buyers and sellers are allowed to go to each other personally and negotiate to reach a successful trade. It somehow limits the information about the bid shout and ask shout to the public. Secondly, the traders in this market microstructure are not allowed to experience the market or learn extensively about the market as the experiment is run only for one trading period. In short, the market microstructure of Chamberlin limits the availability of full information on one hand and restricts the learning of traders on the other. Both reasons cause the DA market results to be not fully matched with the predictions of competitive market theory.

Smith (1962) tries to incorporate the assumptions of full information and learning of traders in the DA experiment. For this purpose, he changes the market microstructure by allowing the traders to announce their shout prices openly in the market. To address the limitation on learning of traders, trading periods are increased from one to eight in the early experiments of Smith (1962 and 1965). At the start of the experiment, at one point in time, a buyer is allowed to shout the bid price or the seller to shout the asking price at which he/she is willing to sell their produce. This price announcement is made public and everyone else in the market gets to know about all the shouts whether it is the bid price from the buyer or the ask price from the seller. If at the announced bid (ask) price the trade is only possible if any seller (buyer) wants to sell (buy) the product at this price offer. Trade can only happen if the bid price offered by the seller is greater than the ask price shouted by the seller. It is step-3 in the market trading process as shown in Figure-3.2. Once the offer (bid and ask) prices are shot in the market then there can be two outcomes of it. Either these offered prices are going to be accepted or rejected. If the other trader accepts the offer, then the trade happens at the price offered by the trader first. The transaction price is the price at which the first trader shouts the offer, and the other trader accepts the offer.

In other cases, the offer may get rejected and that may happen because of a very high (low) ask (bid) price by the seller (buyer). If such a situation arises, then the traders return to step 2 unless a new offer comes in the acceptable market and trade happens. So, after the first shout, any trader can shout bid or ask that could replace the existing shout (bid/ask). This is known as the bid-ask improvement rule. According to this rule, any trader can replace the active existing shout in the market by announcing more attractive offers. For example, if initially a buyer shouts a bid price at which he/she wants to buy the product of the seller, but the seller accepts it then the next buyer can overcome the existing bid price by offering an even higher bid price. On the other side of the market, a new seller can overwrite the existing offer price at which he/she wants to sell the produce. To improve the existing offer price, another seller from the market may offer to sell the same product at a lower price relative to the prior seller.

Once the buyer with the maximum active bid is greater than the existing ask price by the seller then the trade happens at a price equal to shout who enters the market first. Smith's microstructure of the DA market is a bit different from what is followed by Chamberlin (1948). Chamberlin, as explained, follows a market structure where traders try to engage privately with each other. In this trading environment, there is a limitation on the availability of full information. Additionally, traders have limited learning about the market environment. But in the market structure of Smith, as all offers (bid and ask) prices are shouted publicly, so every trader has access to information about the whole market at each point in time. On one hand, it increases the competition among the traders to grab the opportunity by improving the bids and asks[12]. On the other, it also improves the learning of traders as all traders have access to information regarding all bids and asks. This extra information about the market helps the traders to learn more quickly about the market structure than traders are expected to learn in the Chamberlin market.

Additionally, in Smith's market, there are more than one number of periods where each buyer and seller have constant values and costs respectively. In this market, there is a constant competitive equilibrium price and quantity level in the market across the periods. It is the reason, that in Smith's DA market, human traders got more chances to learn about the market structure and more chances of making higher profit margins. Experience and learning processes are considered crucial in DA experiments to help traders gain more surplus by making rational decisions. It is because of the learning process that the traders can assess the market environment and make decisions that could lead to higher market efficiency. These two reasons for larger access to information and trade

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[12] Improvement of bid and ask shout prices means to increase the decrease price (that shows the willingness of buyers to buy at higher price) and to decrease ask price (which shows sellers are willing to sell their produce at lower price).

across periods with the same values and costs cause high price convergence to equilibrium price and high market efficiency as compared to Chamberlin.

So, the main difference between the market structure of Chamberlin and Smith can be seen in step-2 & step-3 of Figure-3.2 & Figure-3.3. In Chamberlin, traders go physically to their counterparts to look for trading opportunities while in Smith, all the shouts from all traders are being announced publicly and all traders can shout counteroffer at any time. According to Smith (1962), these differences are due to more access to the market, relatively high information availability, and more learning experience in the market across periods with the same market structure.

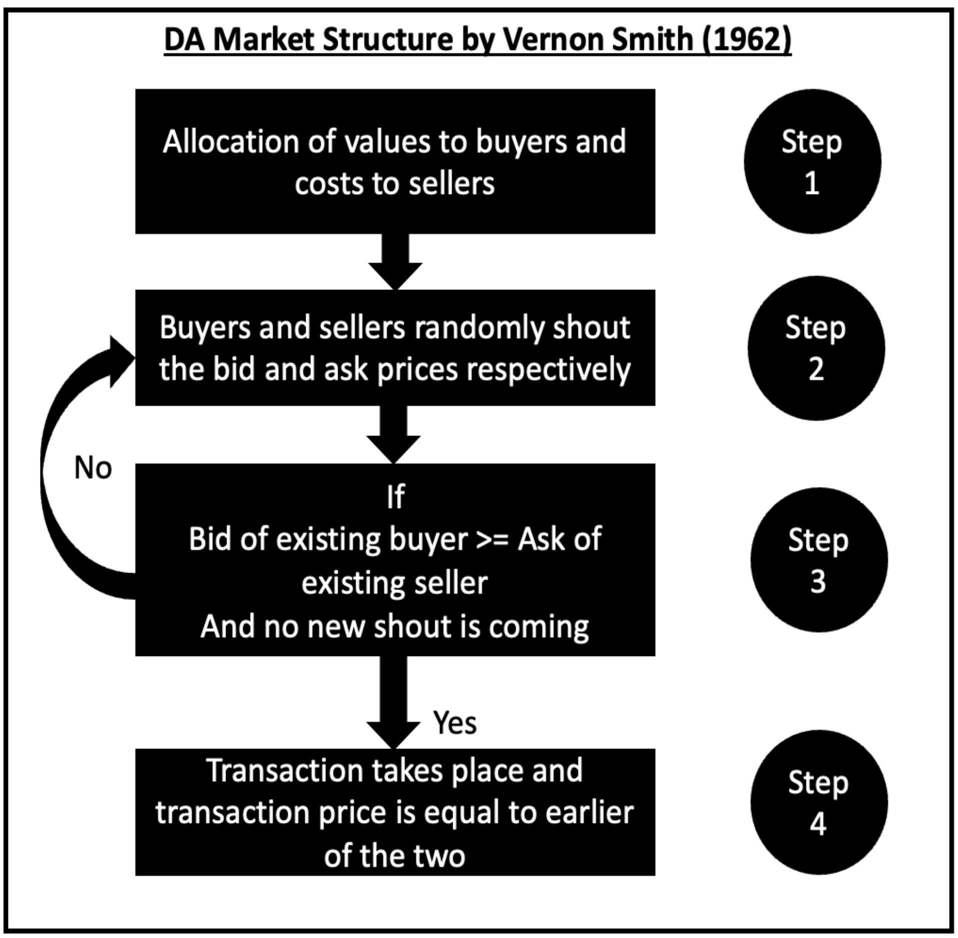

Figure 3.3: ODA Market Structure by Vernon Smith (1962)

Results from Chamberlin (1948) and Smith (1962) help to conclude that the market microstructure used in the experiments affects market efficiency. This microstructure is useful in achieving market efficiency even after controlling for some assumptions of the competitive market, such as a large number of buyers and sellers and full information. Interestingly, the experimental market results offer to provide the predicted results of competitive market theory even when the assumption of a large number of buyers and sellers is relaxed. It is done by running the experiments in a class with a small number of traders as the DA market of Smith provides the required results as the theory predicts. The second assumption of full information is ensured partially by providing access to information about bid and ask shouts publicly[13]. It leads us to conclude that in human-populated DA market experiments (especially the market structure of Smith) the theoretical predictions are validated even when the assumptions of the large number of traders and full information are relaxed.

3.5. DA with Zero Intelligence Traders

The critique on the DA experiments, by Chamberlin (1948), Smith (1948), Gilson (1982), Becker (1962), and others, with human traders revolves around the ability of traders to learn about the market dynamics as the market evolves over the trades. The traders also change their behavior when they learn and get experience to earn maximum gain from trade. It is considered that the results of these initial experiments are dependent on the learning mechanism of traders. Critique is made of the DA results as these are not solely due to the market itself that can lead to high market allocative efficiency and price convergence. One of the major reasons for this critique is to keep the market demand and supply function constant over the trading periods. If these redemption

[13] In Smith's market structure although the traders are allowed to have more information but still it was not full information. It is because of private information that every trader has as on its basis information they shout offer prices. In addition, the traders also don't know about how many quantities are available, what is the market equilibrium price and how much maximum surplus they can extract.

values to buyers and costs to sellers are constant, then the traders learn very quickly about the market. Such market microstructure is not in line with the real-world market. In real markets, with each passing trading period not only do new traders come into the market but their redemption values and costs also keep changing. It makes the real market more complex, and traders are unable to learn about the market dynamics even when they remain in the market across periods. Human-populated experiments provide results closer to theoretical prediction when this change in demand and supply functions are kept constant as it ensures the learning of traders. It is why the initial results of DA, by Chamberlin (1948) Smith (1962 and 1965), Becker (1962), Isaac and Plott (1981), and others, are criticized due to the significant role of human learning in these experiments by controlling the market environment. So, these results are made possible by keeping the market microstructure constant and repeating it many times so traders can learn about it and make rational decisions. It is the result of this learning mechanism of traders in the human-populated market that the price convergence is made possible by the experimenter.

Then the question arises about the importance of learning in the DA market. The learning of traders is linked to the rationality assumption of the competitive market. If the trader is learning about the market over the trade and the overall market surplus is improving, then it means learning is happening. To check this proposition, it is necessary to control the learning behavior of traders in the experiment. Now there was a need to check if the market efficiency is due to the learning of traders or if it is because of any built-in mechanism of the market. This analysis requires segregating the role of the market from learning behavior by controlling the learning of traders. Until or unless the human traders are involved in the market experiment the experimenter is unable to control the learning process altogether.

In response to this market assessment, Gode and Sunder (1993, 2003, and 2018) introduce another variant of DA with an artificial market having simulated agents instead of human traders. These artificially simulated agents are known as Zero-Intelligence (ZI) agents with no human-like intelligence and hence no learning system at all. The purpose of introducing these ZI agents in the market is to control the assumption of rational decision-making by controlling the learning of traders. It helps to examine if the price convergence towards equilibrium in earlier experiments is due to the rational behaviour of traders as they learn how to behave in the market over time. The results of Gode and Sunder are based on the market structure given in Figure 3.3. This market structure looks very appealing in the sense that it mimics Smith's market but with ZI agents instead of human traders. Results from the market microstructure of G&S show that even without rational decision making the market provides outcomes in line with predictions of competitive market theory. However, when analyzed in detail, several questions arise in the market structure of Gode and Sunder that may affect the market efficiency. Due to these differences in market structure, the DA simulations by Gode and Sunder lead the market closer to theoretical predictions. These results help us understand whether price convergence and market efficiency are achieved even after controlling for human learning. Alternatively, they may show whether the market structure is responsible for the DA experiment achieving results predicted by competitive equilibrium theory.

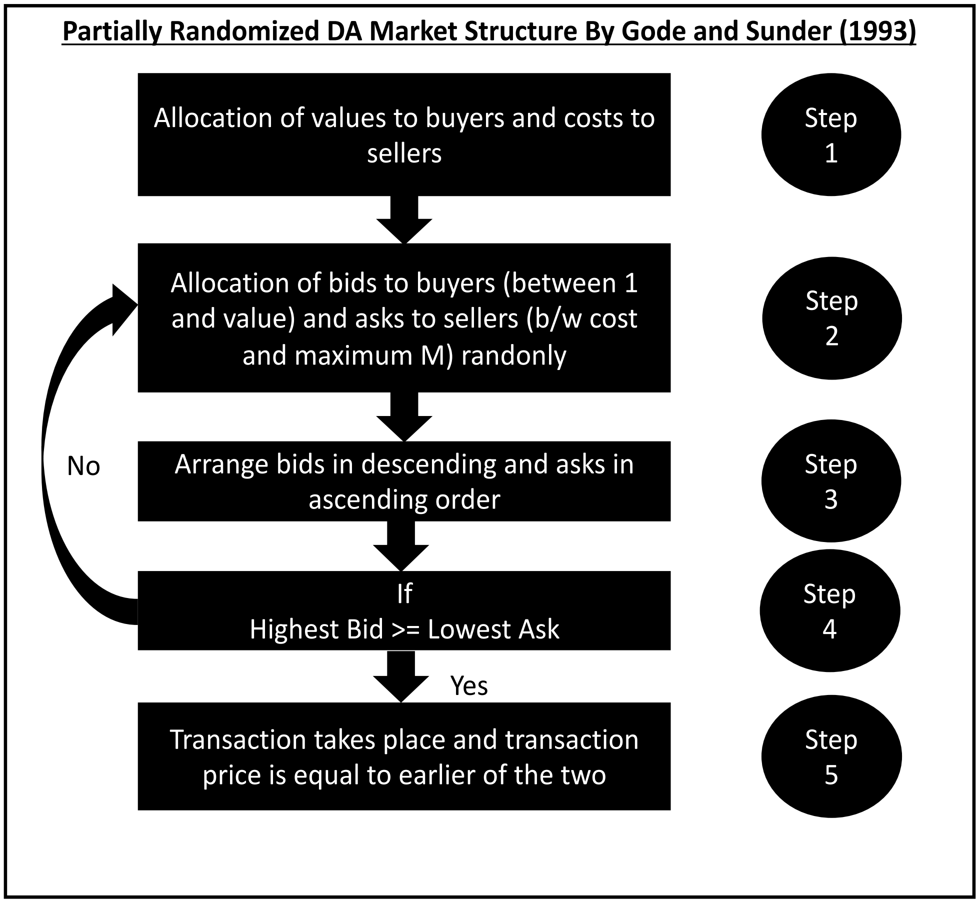

Figure 3.4: Randomized DA Market Structure by G&S with ZI Agents [Source: Author's own]

One of the points that differentiate the market structure of G&S from that of Smith, is the random allocation of shout price in the DA experiments. If we analyze the market structure of how the agent trades in ZI populated market of G&S as compared to the human-populated market of Smith, then it is realized these two markets are structured differently. In the simulated market of G&S, the traders are assigned redemption values and are also told the minimum value they can charge. The range to select the shout price is determined first. The upper (lower) limit is defined as the redemption value (cost) of the buyer (seller) allocated at the start of the simulation and the lower (upper) value is the minimum (maximum) value at which the buyer (seller) may want to buy (sell) the good. The bid (ask) price is selected from this range of minimum (maximum) value and the redemption value (cost) randomly. The minimum value to bid and the maximum cost to ask are selected by the experimentalist[14].

Now in the G&S market structure, as illustrated in the chart above, all the traders are allocated the shout prices randomly between a range. For buyers, the bid price is selected as a random number between the redemption value of that specific buyer and a minimum value selected. This redemption value is allocated at the start of the experiment to each buyer, and it remains constant over the period. The same is the case with the seller's ask price. The Ask price for each seller is selected randomly between the cost of that specific seller and the maximum possible ask price (Step 2 in Figure 3.4). It means that the buyer who has the highest redemption value will have the largest range to select the bid and more possibility to shout a higher price. This is because the range of other possible buyers is smaller. For example, in Appendix 1 buyer 1 has a redemption value of 325, and that buyer can select any bid price between 1 and 325. Whereas buyer 11 who has a redemption value of 75 can select the bid price from a range of 1 and 75. It means that buyer 1 has more chance to randomly select a bid price higher than the random bid price of buyer 11. So, the buyers with higher redemption values also have more chances to have a higher bid price and steal the deal first. The opposite is the case for the sellers as the seller with cost has more chance to trade first by shout a lower ask price as compared to the seller with higher cost.

Once the bid and ask prices are selected randomly by all the simulated agents in the artificial market, then all these agents are arranged to check which of them are the most potential candidates to trade. Arranging the buyers and sellers in terms of their bid and ask prices helps to select the buyer who has the highest willingness to pay among all the buyers and sellers who want to sell

[14] In simulation of Gode and Sunder (1993 and 1997) the minimum value of bid price can be 1 and the maximum value of the ask price can be 200. But there is no theoretical support about how much should be ranged to select the shout prices.

their produce at the minimum price. This sequence of arranging the buyers in descending order for their bid price and sellers in ascending order for their ask price is known as the Marshallian Sequence. It is because of this sequence of ZI agents that the results of G&S match with the results of early experiments.

Intuitionally, it's evident that the ZI buyers who have higher redemption values also have a higher chance to be randomly allocated higher bid prices to shout. Whereas the opposite is true for the buyers with lower redemption values. On the other side of the market, the seller with lower allocated costs has a higher range to randomly select the ask price as compared to sellers with higher allocated costs. It can be illustrated by providing more detail on how the ZI-populated artificial market is designed to work by G&S. For this purpose, the pseudo-code of the market trading mechanism is illustrated here.

Box-1: Pseudo Code for ZI Simulated Market by G&S [Source: Author's own]

The following steps are followed in the artificial market of G&S populated by ZI agents.

1. A required number of ZI agents are selected for the simulation. All the generated ZI agents are then divided between buyers and sellers. Depending on the market microstructure the experimenter follows, the number of buyers and sellers may be equal or unequal in the artificial market.
2. All the buyers are allocated redemption values. This is the maximum value of the good for the buyer, who wants to buy it at a price lower than this value. All sellers are allocated costs. This is the cost incurred in the production of the good, and the seller wants to sell it at a price higher than this cost.

3. A random bid price is selected for all the buyer (i.e., from the range of minimum value they want to pay (1 in this case) and their redemption value). Similarly, a random ask price is selected for all the sellers (i.e., price between their respective cost and maximum price they can charge for the product (200 in simulated market of G&S)).
4. Once all the agents are allocated the bid and ask price then they are arranged in accordance with Marshallian Sequence. All the buyers are arranged in descending order according to their bid prices. The buyer with the highest bid price is ranked first, and the buyer with the lowest bid price is ranked last. Sellers are ranked in ascending order based on their ask prices. The seller with the lowest ask price is ranked first, and the seller with the highest ask price is ranked last. This list of buyers in descending order and sellers in ascending order showcase the active buyers and sellers in the market who are willing to go into trade.
5. From the arranged set of agents in the last step, the bid price of the first buyer (or the buyer with the highest bid price) is compared with the ask price of the first seller (or the seller with the lowest ask price). In other words, the buyer with the highest bid price and the seller with the lowest ask price are selected to determine if they are eligible to trade.
6. If the bid price of highest bid buyers is greater than the ask price of lowest ask seller, then both agents are eligible to make the trade.
7. The trade happens at the shout price of the agent who enters the market and shout the price first. If the highest (lowest) bid (ask) price buyer (seller) enters the market first the trade happens at the price shout by that specific buyer (seller). This price at which both agents agree to trade is the transaction price of the contract price.
8. Once the trade happens between the buyer and seller then both these agents satisfy their need to come to the market. So, after the transaction happens both agents, who got successful in making transaction, goes out of the market.

9. When these successful agents go out of the market then the comparison is made between the bid price of second highest buyer and ask price of second lowest seller from the active list of remaining buyers and sellers. Again, the comparison is made to check if the bid price is greater than the ask price of top buyer and seller in the active list of agents.
10. But in step 5, if the shout of highest bid buyer is not greater than the shout of lowest ask price seller then the possibility of having trade is not there. In that case, the market goes back and repeats step 4 in this pseudo-code. New random shout prices are allocated randomly again to all the traders while following the constraint mentioned in step 3. Depending on the new shout prices, all the agents are arranged again with respect to their role (either buyer or seller) and their shout (bid or ask) prices. A comparison is then made as explained to check if top of the list buyer has bid price more than the ask price of seller located at top (or with lowest ask price).
11. This process is kept repeating unless there is no active buyer or seller in the list or bid price of no buyer is greater than or equal to the ask price of any of the sellers.

The results of Gode and Sunder's simulations are compared with the results of experiments with human traders. It is found that the surplus in simulations of G&S decreases over the trades but not as speedily as it decreases in human experiments[15]. The Gode and Sunder results show that replacing human traders with ZI agents can control human learning completely. Despite this, the markets still provide results in line with the predictions of competitive market theory. While explaining these results, they conclude that human rationality is not necessary as markets can

[15] In the simulation of Gode and Sunder (1993), the simulations with ZI populated agents is done with two types of market mechanisms. In the first market mechanism, ZI traders faces no constraint to select the shout price. It means any buyer can select the shout price between their redemption value any minimum number. Similarly, any seller only has the minimum value of range i.e., their cost but they can charge as high price as much they want. These are called unconstrained ZI agents. Second type of traders are known as constrained agents where the buyers have to select a bid price to shout randomly between 1 and their redemption value while the sellers have to select the ask price between their cost and maximum value of 200. Because in real world market, normally no trader can make abnormal profit in the competitive market, so we are only considering here to compare the results of constrained ZI agents with the human traders.

achieve the maximum surplus and price convergence even in the absence of rational decision-making traders.

These results of Gode and Sunder (1993, 1997, and 2003) are highly acknowledged in the field of agent-based modeling and experimental economics by accepting the role of free markets in producing the best possible results. However, the results of G&S don't answer all the questions by just controlling the learning behavior of traders. It is still to be explored what are the reasons that markets are reaching maximum surplus and price convergence toward competitive equilibrium price level. If these results are considered absolute in this domain, then the role of learning vanishes altogether and there is no need of traders to be rational. Then it will be just enough to let the markets free work without any intervention, and it will provide the best possible results.

This dissertation aims to shed light on the role of market microstructure in leading the market to achieve results predicted by competitive market theory even without assuming a large number of traders, full information, and rationality. To pursue this purpose, this research tries to look into the factors by exploring the market microstructure of G&S in more detail. To achieve this objective this study proposes an alternative market microstructure while using the same market demand and supply. The motivation behind introducing and testing alternative market microstructure is that the trading mechanism of agents in the ZI-populated market is built in such a way that it leads to higher efficiency. To understand this point, it is imperative to first describe how the trading mechanism works and why it is important to impact market efficiency.

The next section of the literature review explains the significance of competitive market theory. It covers how the theory evolves and what methods have been used over time to prove market efficiency. The section also discusses how the predictions of competitive market theory are verified using different techniques. Additionally, it examines the role of double auction experiments and simulated agent-based models populated by ZI agents. Finally, it highlights the importance of learning in achieving the outcomes predicted by competitive market theory.

CHAPTER 4

RESEARCH METHODOLOGY

The research methodology adopted in this research aims to target the research objectives directly and answer the research questions. The theoretical framework discusses why the microstructure of the market is important in bringing the results in line with the predicted outcomes of competitive market theory. It is deliberated earlier that the market microstructure of Gode and Sunder (1992 and 1993) follows the Marshallian sequence. Based on the market that follows the Marshallian sequence of trading, Gode and Sunder conclude that even without the learning of human traders, the market can achieve the desired outcome. Rationality is not needed at the micro-level in the market but the invisible hand in the market phenomenon is robust enough to lead the market toward efficient results. To test this strand of theory about the efficiency of the market independent of rationality and learning, this study offers alternative market trading environments to check the robustness of ZI results.

4.1. Randomized Trading in the DA Market

The double auction market mechanism of the ZI traders is supposed to have a randomized allocation of shout prices for buyers and sellers. But the randomization should not only be limited to allocations of shouts but also the randomization should be in trading mechanism. ZI traders were initially arranged as per the Marshallian sequence that maximizes the chances of the highest value buyer to have the highest bid and the lowest cost seller to shout lowest ask price. This enforced allocation of shout prices limits the role of randomization in work. This is why the results of these initial ZI traders are also questioned on their accuracy. For this reason, an alternative market structure is developed here that overcomes this issue of limited randomization in the ZI traders' market.

This purpose is achieved by introducing a market structure that possesses characteristics of randomization at two levels: first, randomization in the allocation of value and costs to buyers and sellers respectively, and second, randomization in matching of buyers and sellers to trade with each other. The market structure for this market is illustrated in Figure 4.1. If the market structure being offered here is compared with the market structure of Gode and Sunder (1992 and 1993) then the main difference is in Step 3 and Step 4 in Figure 3.3 and Figure 3.4. In the case of Gode and Sunder, once the allocation of values and costs is done for all the traders then they randomly select the bid price (from a range of 1 and their redemption value) and ask price (from a range of cost and 200). Once the bid and ask prices are allocated, the agents are then arranged in an order as described in Step 3 of Figure 3.4. It is this allocation of agents that produces results in line with competitive market prediction. For this reason, we here propose to change the market structure by allowing the agents to trade randomly with each other without knowing who has the highest willingness to pay and lowest willingness to ask. This purpose is served by altering the market structure of DA at Step 3 when the haggle randomly searches for the best counterpart.

The purpose of changing the market structure by altering the trading sequences of agents is to see if the markets always lead to a competitive outcome or if it is because of any special market structure that makes it happen.

To analyze the role of market structure in facilitating market efficiency, this research uses ZI traders with the same demand and supply functions. It employs an identical number of agents and an equal number of trading periods. The process of selecting the transaction price is similar in the artificially simulated market. All the simulations are done in a ZI-populated market as of Gode and Sunder to make the results more comparable and analyze the differences that may be generated from altering the market structure.

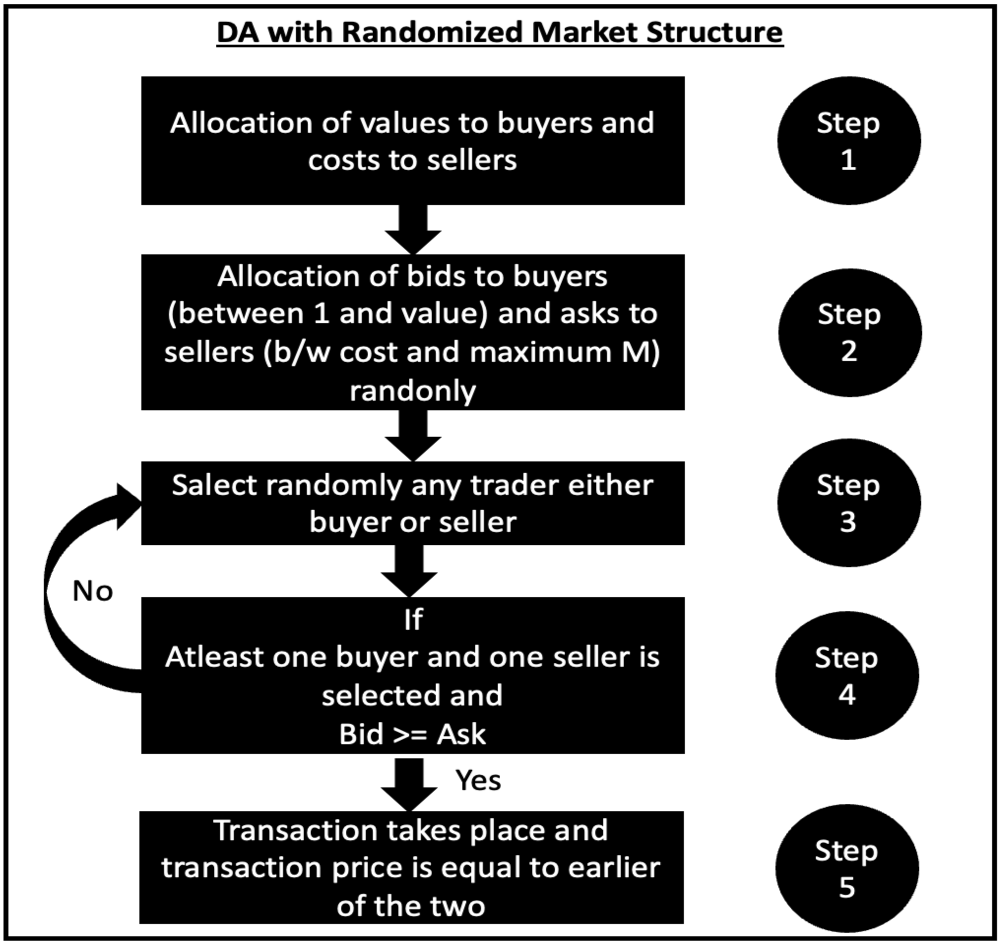

Figure 4.1: Alternative DA Market Structure with ZI Agents [Source: Author's own]

Before going into the details of the DA market randomized market structure, the duplication of results of Gode and Sunder is done in Python[16] while adopting the same market structure and all the details[17]. Once we reach the results the same as the Zero-Intelligence model provides, it makes sure that all the programming in Python is done correctly and the microstructure leads to the same speed of price convergence, the declining surplus over the trades, and the market efficiency.

[16] Python is used because of the flexibility it provides to introduce/allocate agent specific details at micro level.
[17] Market mechanism used in duplication of ZI model, is same as provided in Box-1.

Afterward, the changes in the market structure of the baseline model are possible to introduce to examine how these changes reflect in the market outcome.

Once the baseline model of the DA market populated with ZI agents following a Marshallian trading sequence is constructed then the next step is to introduce new changes in the model. The purpose of bringing changes is to examine the role of trading sequence in the DA market framework. To achieve this purpose, a new ZI model an alternative trading sequence is introduced that doesn't follow the Marshallian sequence. This ZI model introduces an alternative trading sequence known as the 'Randomized Trading Sequence'.

In other words, here we just replace the old trading sequence of the DA market populated with ZI agents with a new trading sequence while all the other details remain the same. Other factors include the demand and supply function of buyers and sellers, the system of random allocation of bid and ask prices, and the randomized entry of traders in the market. The only difference is that in this randomized trading framework agents are not lined up in accordance with their bid or ask shouts, but they are going to haggle randomly in the market. Then the same rule of transaction is applied i.e., the transaction happens if the bid shout of the buyer is equal to greater than the ask shout of the seller. If this condition is met, then the transaction price is set equal to the shout price of the trader who enters the market first.

If the difference in the trading mechanism of the Partially Randomized DA market by Gode and Sunder (1993, 1997, and 2003) is compared with the newly introduced Randomized DA Market, the differences in their workings can be depicted. These differences are reflected in the mechanisms of the two market microstructures. The only difference that we focus on is in points 4, 5, and 6 of these two pseudo-codes. For this reason, here we have mentioned only the changes that are introduced in the alternative model in Box-2 of the market mechanism instead of reproducing the whole code again.

Box-2: Mechanism for Alternative Randomized ZI Simulated Market

The following steps are modified in the alternative randomized trading sequence introduced here.

4. After allocating bid prices to buyers and ask prices to sellers randomly from a given range, the agents are allowed to enter the market. The range is specified differently for each agent depending on their redemption values and costs.
5. It may happen that if randomly a seller enters in the market, then the next agent may also be a seller. This iteration keeps repeating until a buyer enters in the market. Now once there is at least one active buyer and at least one active seller in the market, their bid and ask prices are then compared. If the bid price of an active buyer is greater than any randomly chosen seller, ask price in the market then the trade happens. Otherwise, this process of haggling of agents in the market will keep repeating to give chance to agents to explore the possibility of trade with any other counterpart.
6. From this iteration if no agent has been successful in fulfilling the criteria, then this whole process will be repeated. If no buyer or seller has been successful in making a trade or not fulfilling the criteria to be eligible to trade, then the chance is given to the new agent from the list of inactive agents. The new agent is then randomly chosen from the list of all the inactive agents. This point is now addressed in the thesis by provided additional details. In this way trade happens between randomly chosen agents to whom the shout prices are allocated randomly, and they enter in the market randomly. For each trading period, this process of haggling or entering of new agent in the market will be repeated until there is no inactive agent, and all the agents gets their chance to trade. When all the active agents are not able to make trade[18] then the trading period ends.

[Source: Author's Own]

This DA market trading framework helps to examine the performance of the market mechanism while controlling all the factors except the trading sequence. Or it helps to evaluate the impact of

[18] All the active buyers and sellers in the market may not be able to find potential trading partner if all of them does not meet the criteria to trade i.e., highest bid price of buyers is lower than the lowest cost seller.

trading sequence on market performance. This simulation of an artificial market populated with ZI agents will help examine several factors. It will assess whether price convergence, the decreasing bid-ask spread over trades, and market efficiency change or remain the same. This is evaluated when only the trading sequence changes, while all other details of the market microstructure remain constant as in the baseline model. It will help us to compare the results of the newly introduced model and if market simulations still lead to the same conclusion, then two hypotheses can be confirmed. First, the invisible hand metaphor works not only in a market populated with human traders but also in a market populated with ZI agents. And second, the hypothesis is the necessity of markets to have rational traders for an efficient outcome. If an alternative ZI-populated market simulation still provides the results predicted by competitive market theory after changing the trading sequence, then it means markets may not need to have rational agents. Rationality at the micro-level may not be required to have efficient market outcomes at the aggregate level.

It is this proposed alternative randomized trading sequence that all the traders get an equal chance to enter the market and see their eligibility to trade no matter what their redemption values or costs are. This trading sequence differs from the Marshallian Trading sequence. In the Marshallian Trading sequence, which was first applied by Gode and Sunder (1993, 1996, and 2003) in ZI-populated artificial markets, intra-marginal traders are allocated shout prices. These traders are then arranged in a way that maximizes market efficiency. But in the alternative trading sequence, the arrangement is not enforced on the agents dictating to them who enters the market first and which two agents must trade with each other. In other words, the scope of negotiation, making mistakes, learning, and getting market experience is just not there.

Once the role of the trading sequence is examined for the double auction market by introducing a new randomized trading sequence, we will be able to find out if the market mechanism works by itself and leads the market to equilibrium. If the results of the alternative random trading sequence are just like the results of the Marshallian sequence in the DA market, then it means that the trading sequence doesn't have any impact on the market outcome. In that situation, altering the trading sequence still provides an outcome in line with the expected outcomes of competitive market theory.

But, on the other hand, if the results of the DA market with a Randomized trading sequence are different from the results of the Marshallian trading sequence, then it employs the significant role of trading sequence in the DA market. It then provides strong evidence that the markets don't always provide an efficient outcome, but it depends on the details used in the microstructure. It also employs that phenomenon of free market under demand and supply forces doesn't always ensure efficiency. Now if the market forces alone are not enough to make the market itself efficient then it means other elements play the role. These associated market elements are controlled or ignored in the initial artificial DA markets while concluding that market forces do not require anything but a free environment to work by itself. It is an extraction from the same concept, it is deduced from early simulations that the rationality, experience, and learning of agents is not needed but markets are "always" efficient.

Taking forward our argument based on the results of the Randomized trading sequence, market efficiency is not universal but is subject to its microstructure i.e., mechanism, environment, and other related details. If the result of this study establishes the significant role of trading sequence in making the market efficient and in the price formation mechanism, then results support that the market microstructure is important to consider. The early results of ZI simulation then also need to be reconsidered by considering the reasons or factors that make the market efficient as now it's not the result of the free market phenomenon. Here comes the role of individual rationality. The reason for incorporating rationality in the simulation is to make the market efficient for different microstructures. This is due to the failure of demand and supply forces to achieve market efficiency. Specifically, these forces do not set the equilibrium price at the level that maximizes allocative efficiency. This is why, the next devotes to explaining the methodology used in affirmation of the learning mechanism of ZI agents.

4.2. Learning Mechanism of ZI Agents with Marshallian Sequence

The previous section explains the methodology for testing the importance of market microstructure by presenting an alternative trading sequence to the Marshallian sequence. If the results of the alternative trading sequence differ from the early outcomes of ZI-populated markets, then we can conclude that the market alone, without specific microstructure details, is not sufficient to produce results as predicted by competitive market theory. This is illustrated by Cliff and Bruten (1997) with the phrase 'Zero is not enough'. This means that controlling all factors involved in experiments, such as experience, learning, rational decision-making, and bargaining, and relying only on demand and supply forces is not enough to make markets efficient. The result of Cliff and Bruten (1997) has huge importance in reviving the importance of rationality in the market phenomenon instead of just controlling and ignoring it. The way they reached this result is quite different. Cliff and Bruten changed the demand and supply functions used in the initial ZI-populated market of Gode and Sunder (1993 and 1994). They introduced asymmetric demand and supply functions (commonly known as Box-shaped demand and supply) to show ZI populated simulated market does not provide results in line with the competitive market outcome. On this basis, they introduce a complex kind of learning mechanism for ZI agents and call them Zero-

Intelligence Plus (ZIP) agents. Whereas this research tries to provide new evidence for the same argument that zero intelligence is not enough by replacing a universally used Marshallian sequence with a pure Randomized trading sequence.

Here, the first and foremost step is to replicate the model of Cliff and Bruten. This involves using the same microstructure that was used in their research to evaluate the importance of the learning mechanism in DA simulations. Cliff and Bruten (1997) used the same microstructure as in Gode and Sunder (1993 and 1994), except that their ZI agents can learn about the market with experience. The trading sequence following Cliff and Bruten (1997) is also a Marshallian sequence. Cliff (2021) also uses the same trading sequence while focusing on the learning of agents when they face very limited time to trade. According to Cliff (2021), there is a trade-off between the time available to trade and the market surplus the agents can extract from the market. The concept behind this trade-off is motivated by the human-populated DA market. Traders are anxious to trade for two reasons. First, they want to find the best suitable counterpart to maximize profit. Second, they want to avoid the chance of not being able to trade at all if the trading period closes. (Chen, 2017). To make a trade and become more eligible for it, market participants usually make shouts while trying to maximize profits. However, as time passes and they learn about the market, they start decreasing their profits. Buyers begin improving their bid prices, and sellers start decreasing their ask prices. It is due to the limited time available to make the trade that the traders start decreasing the surplus to trade and make a profit.

Furthermore, Cliff (2021) highlights another factor that has a significant impact on the learning behavior of agents over time. It is the limit prices set at the start of the experiment for the agents to consider while announcing the shout prices. The buyer's limit price is the minimum price that may want to pay for the product, while the seller's limit price is the maximum price they may want to charge. In the experiment of Gode and Sunder (1993), the limit price of the buyer is 1 while for the seller it is 200. Here questions arise about how these limit prices are set, and what is their impact on the decision-making of traders, their learning behavior, and their rationality. For instance, if the limit price of sellers is very high then the sellers are allowed to make shout prices from a range between their cost and maximum limit price. Owing to the high price limit, the range from which the agent selects the price, also increases. It will have an impact on the learning behavior of the agents as now agents will require more time to learn about the price suitable to trade and at which they can earn maximum profit. So, the learning speed is inversely proportional to the range of agents who must select the shout price. The same is true for the buyers. Cliff (2021) provides an updated version of ZIP agents. He mentions an inverse relationship between the time allowed for agents to trade (ticks or iterations in simulations) and the range from which agents can select the shout price. Focus has been on the limit prices set exogenously for all the agents in the simulations.

Although these exogenously set limit prices have a significant impact on the learning behavior of agents, our focus here is more on the trading sequence used in the microstructure of these artificial markets. As discussed, the first step here is to imitate the learning model of ZIP agents that uses the same trading sequence as ZI traders (illustrated in Figure 1.3). Here the major focus has been on the learning rules the agents follow to improve their shouts so they can make maximum gains out of trades. ZIP agents also follow the same trading rules as applied to ZI agents i.e., the Marshallian sequence of trading.

By incorporating the learning rule in ZI agents, we transform them into ZIP agents who can learn from their environment and improve their shout price to be more eligible to trade. Appendix I provides the demand and supply used by Cliff and Bruten (1997). Once we imitate the ZIP-populated model of the DA market that follows the same trading rules as the ZI agents, we can introduce variation. The purpose of bringing in new variations in the simulation is again the same for the ZI-populated market, that is, to test the market outcome by changing the market mechanism. The focus has been on the trading sequence of the market to check if ZIP traders, who can learn about the market, accomplish market efficiency if they trade in different trading sequences.

The ZIP agents of Cliff and Bruten (1997) and Cliff (2021) use a market microstructure following the Marshallian Path, yielding higher market efficiency compared to Gode and Sunder's ZI agents (1993, 1997, 2001). However, these results are sensitive to various market factors, including the range of shout price selection and trading sequence. To address this, we propose an alternative randomized trading sequence with ZI agents learning about the market.

This is the second phase of testing the importance of market microstructure in the DA market environment. The first attempt is to apply an alternative trading sequence for ZI agents with no intelligence; hence, there is no rationality or learning mechanism. If the results of an alternative randomized trading sequence differ from the trading sequence used by Gode and Sunder (1993 and 1997), we can conclude that the market itself does not lead to an efficient outcome. Once these results are obtained, the introduction of intelligence to the agents is mimicked, as in Cliff and Bruten (1997) and Cliff (2021). Afterward, we intend to test the DA market populated with agents who can learn about the market environment. It helps to figure out if the learning mechanism of traders proposed in the literature is helpful in always achieving market efficiency.

4.3. An Alternative Learning Mechanism of ZI Agents

The results of ZI agents have been embraced in the field of experiments and microeconomics. However, soon after these results were presented, literature showed that ZI results could be further improved. This improvement occurs if agents are allowed to learn about the market environment.

In this regard, the learning mechanism is embodied in the ZI agents to allow them to learn about the market and revise their shout prices accordingly in the coming periods. This purpose is achieved by assuming numerous types of algorithms to learn ZI agents. The first was introduced by Cliff and Bruten (1997), who proposed a very complex learning mechanism, as explained in the last section (Appendix 2). Later, Preist and Tol (1998) state that the ZIP agents introduced by Cliff and Bruten (1997), although they have very high efficiency levels, assume a simple learning heuristic for the agents[19]. The learning rate and all related values of coefficients used in these learning mechanisms are assumed while focusing on the maximization of surplus.

Later, Gjerstad and Dickhaut (1998) offered another type of learning mechanism that was even more complex than the ZIP agents. They develop beliefs applicable to all agents. The major point of their learning rule is that agents learn by communicating with other agents in the market. They improve their shout prices based on information they obtain by communicating with other agents and from past periods. Here again, all the details about the communication that helps the agents to learn, are assumed as all coefficient values do not come from any human-based heuristics or experience. Another trading strategy used in the learning process is wait-watch-grab, which means waiting and watching while other agents are shouting and improving prices and grabbing the deal as soon as the shout price is in accordance with the agent's belief. This learning and trading strategy was introduced by Kaplan, and these agents were later known as Kaplan agents. This is a sniping strategy that exploits competing traders. An issue with this learning mechanism is that Kaplan traders may become successful in a few trades. However, once others learn about their strategy, the Kaplan traders are forced to leave the market due to their exploiting behavior. Similarly,

[19] The agents with learning mechanism of Preist and Tol (1998) are known as Persistent Shout (PS) agent they learn about the market and adjust their shout prices but with a momentum coefficient that is randomly chosen from a given range.

another learning strategy is known as Genetic Programming (GP), and GP agents are given a pool of different strategies. Every GP agent can move to another strategy in the next period to improve their performance. Here again, all the given strategies available to agents are complex and assumed by the experimenter, but do not come from the experiments. Another learning mechanism is the Bayesian Game Against Nature (BGAN), in which agents revise and update their belief system from the distribution of the shouts of other agents.

The number of learning mechanisms introduced in the literature is even greater than that discussed above. However, there are a few major concerns regarding these mechanisms. First, these markets with learning agents assume learning rules by themselves instead of borrowing them from empirical results, experiments, or real market data. Second, all the learning mechanisms are so complex that they are very hard to understand, let alone follow in the actual trades. Therefore, learning rules were extracted from the experimental data. Although there are separate theories on how human traders learn about the market, there is no evidence that applies the rule extracted from human traders to ZI agents. There are the number of theories on human learning i.e., Regret Theory and Directional Learning theory.

The empirical results from the literature can be divided into two extremes regarding the learning mechanism in the DA market. One strand focuses on the learning of humans and develops advanced theories on it, whereas the other applies complex fictional learning models to ZI agents[20]. However, no study has been conducted that extracts the learning rules from human traders and applies these learning rules to ZI-populated agent-based models. The most effective way to bridge the gap between experimental economics and agent-based modeling is to extract the rules from

[20] Here the point tried to make is that in literature most of the learning models are not based on the actual human experiments but assumed learning mechanisms are applied that maximize the market efficiency without considering if these mechanisms are followed by traders or not.

human population experiments and study the agent-based model based on these rules. Therefore, the aim should not be to construct an artificial intelligence model that can provide results in line with competitive equilibrium predictions. However, the objective of artificial markets is to develop such a market, which is based on the rules that run real-world markets. The only way forward is to observe real human behavior in the experiments, extract rules on how they behave (make the trade, shout bid/ask prices, etc.), and then use these rules as the bedrock of the artificial market.

The same methodology was used in the present study. We have attempted to extract rules from experimental findings that involve real subjects. The only constraint to accomplishing this step is to conduct an experiment that provides all the required information regarding the decisions of the participants in the experiments. This information may include the number of participants on both sides of the market, redemption values and costs allocated to all participants, shout prices of all traders, transaction prices on each successful transaction, and the surplus from trade for each successful trader. This information is provided by DeYoung (1993) in an experiment conducted in a double auction market environment. Based on this information, we have extracted the rules based on which traders improve the bid-ask spread, that is, how much the buyers increase their bid price and how much sellers decrease their ask prices to be eligible to trade.

These learning rules are then applied in an artificial market with the same market setting as DeYoung (1993) to confirm if these rules offer the same results as provided in the human-populated market experiment[21].

Box-3: Learning Rule for ZI Populated Simulated Double Auction Market

[21] Different extracted learning rules are applied many times in an artificial market to come up with the same results as of DeYoung (1993) and lastly the rules are finalized that provides same outcome.

The learning rule for the simulated double auction market can be customized in a way that mirrors the results of human traders in the same market with similar market conditions. Before going into details of how the model works, it is necessary here to explain some assumptions regarding the behavior of agents in the market.

Assumptions:

Agents are risk averse. Implication of this assumption is the learning behavior of agents emerges over the trades as they witness the successful trades at the initial shout prices with lower profit margin. Here the risk-aversion assumption imposes a restriction on the agents to decrease their profit margin in the future periods if they are unsuccessful to trade in this period. Traders wants to reduce avoid the risk of being unable to make profit by not going into trade. To avoid this risk, the agents respond by declining the profit margin in the upcoming trades. So, over the periods the agents start with high profit margins but when they see that they are unable to trade at first iteration then they decrease their profit margin on second iteration and so on.

Following steps are followed for the DA market populated with artificial agents and model is developed in Python to reconfirm if the results from artificial agents can replicate the results of human traders.

<u>Step 1:</u>

- Randomly any of the buyer or the seller is selected from the market.
  If at least one of the buyers and one of the sellers is selected, then go to step 2 otherwise keep repeating unless market has at least one of buyers and sellers.

<u>**Step 2:**</u>

- Record the value (cost) for buyer/buyers (seller/sellers) selected in step 1.
- Following approach is used to allocate the ask price to each selected seller and bid price to each selected buyer.

For the selected Buyer:

$$P_{Bid} = \textit{Random Value } [(\textit{Value} * \textit{Profit Margin}), \textit{Value}]. \qquad \textit{Equation 1.a}$$

For the selected Seller:

$$P_{Ask} = \textit{Random Value } [\textit{Cost}, (\textit{Cost} * \textit{Profit Margin})]. \qquad \textit{Equation 1.b}$$

$$\textit{Profit Margin for all Traders} = \textit{Trading Period} * 10\%. \qquad \textit{Equation 1.c}$$

Once all the bid prices for the firms and the ask prices for the laborers is selected then we come up with the following lists of firms and laborers.

$$\textit{Buyers' with bid prices: } b_{i,\,bid} = U\,\{b_1, b_2, b_3, ---, b_n\} \qquad \textit{Equation 1.1}$$

$$\textit{Sellers' with ask prices: } s_{i,ask} = U\,\{s_1, s_2, s_3, ---, s_n\} \qquad \textit{Equation 1.2}$$

Here the equation 1 and 2 shows the range from which every buyer and seller is allocated the bid and ask prices randomly. For instance, every buyer is assigned a bid price randomly between minimum redemption value (which is same for all the buyers and in this case, it is equal to 1) and redemption value allocated to each buyer individually.

Step 3:

- Once the ask and bid prices are allocated to selected buyers and sellers then, over the iteration within each period and across the period as well, these trades have to be improved depending on the agent behavior.

  Here,

  Improve ($B_i(t, k)$, $A_j(t, k)$): Function represents the improvement of trade between buyer 'i' and seller 'j' based on their respective bid and ask prices. Here 't' denotes iteration, and the 'k' denotes the period.

  After the first period, the traders are allowed to improve the shout price. The improvement rule over the iterations within each period and across period is represented by $B_i\,(t + 1)$ and $A_i\,(t + 1)$ for buyers and sellers respectively.

$$B_i(t+1, k) = B_i(t, k) + \Delta_i \qquad \textit{Equation 1.3}$$

$$A_i(t+1, k) = A_i(t, k) + \Delta_j \qquad \textit{Equation 1.4}$$

Here Δ_i and Δ_j represents the increment in profit margin for buyers and sellers, respectively, in response to successful trades.

- In our model, these two shout improvement rules are as follow.

Over the periods: As the agents are risk averse so at the start of upcoming trading period the traders lower profit margins but as the period passes and they witness successful trades they start improving the profit margin over the periods.

$$\textit{For buyers: } profit\_margin_i(0, k) = initial\_margin_i \qquad \textit{Equation 1.5}$$

$$\textit{For sellers: } profit\_margin_j(0,k) = initial\_margin_j \qquad \textit{Equation 1.6}$$

As the period progress, if agents witness successful trades they increase their profit margin.

For buyers:

$$Profit\_margin_i(t+1, k) = \begin{cases} profit\_margin_i\,(t,k) + \Delta_i & if\ Trade\_successful_i = 1 \\ profit\_margin_i\,(t,k) & otherwise \end{cases}$$

For sellers:

$$Profit\_margin_j(t+1, k) = \begin{cases} profit\_margin_j\,(t,k) + \Delta_j & if\ Trade\_successful_j = 1 \\ profit\_margin_j\,(t,k) & otherwise \end{cases}$$

Over the iterations: Within each period, the agents who have not been successful in the making trade in past iteration they decrease their profit margin to be able to make trade.

For buyers:

$$Profit\_margin_i(t+1, k) = \begin{cases} profit\_margin_i\,(t,k) - \delta_i & if\ Trade\_successful_i = 0 \\ profit\_margin_i\,(t,k) & otherwise \end{cases}$$

For sellers:

$$Profit\_margin_j(t+1, k) = \begin{cases} profit\_margin_j\,(t,k) - \delta_i & if\ Trade\_successful_i = 0 \\ profit\_margin_j\,(t,k) & otherwise \end{cases}$$

In these formulas:

- δ_i and δ_j represent the decrements in profit margins for buyers and sellers, respectively, when they do not achieve a successful trade in the previous iteration.
- The rationale behind increasing or decreasing the profit margin in the future periods is based on the experience of traders in the current period. If the traders are unable to make trade in the current period, then they become more desperate to get a successful deal by lowering their profit margins. Similarly, if the traders observe that within each periods their chances of getting into successful trade is declining, they start decreasing their profit margin. The economic background of this kind of traders' behavior is backed by their attempt to increase the utility maximization by getting into trade and earning as much as possible.

Step 4:

Once the buyers and sellers are selected randomly at first step then the following steps are to be followed.

- After the first step of selecting the traders to trade from the list of all buyers and sellers, next step is to compare if these traders are eligible to trade.
- If any of the buyer has bid price greater than the ask price of any of the seller, then they both gets eligible to trade.
- Here if more than two buyers (sellers) have bids (asks) greater (lower) than the ask (bid) price of seller (buyer) then greatest (lowest) of the two will be selected.

Step 5:

- If any of the buyers does not has bid price greater than the ask price of any of the seller (as happened in iteration 1) then the active agents will revise their shout by decreasing and replacing it with new profit margin.

  Revise profit margin (Over the Iteration)$_t$ = $\frac{\text{Profit Margin}_{t-1}}{2}$
- Any of buyer or the seller is selected randomly, as in step 1.

- This process will keep going until any of the buyer has bid price greater than ask price of seller.

Step 6:

- If the bid price of any of the buyer is greater than the ask price of any of the seller, then they get eligible for trade.

Step 7:

- When the trade will happen between buyer of highest bid and seller of lowest cost then both agents will go out of market for that period.
- Trade price is equal to the shout price of trader who enters the market first.

Step 8:

If no trade takes place in any period, then total of 10 iterations are repeated while following the step 4. If still no trade happens then the market gets closed for that period.

[Source: Author's Own]

4.4. Alternative Learning Mechanism: Marshallian VS Randomized Trading Sequence

Once the learning rules are defined for trading in an artificially simulated market, then the next step is to apply this learning mechanism in the double auction market. It is applied in several steps to test the required double auction models.

1. Once the learning rules are established, then these rules are applied for the number of double auction market environments having different demand and supply functions i.e., symmetric, asymmetric, and box-shaped demand and supply functions.
2. These learning rules are applied in a double auction market that follows the Marshallian sequence and then also applied in the market with a Randomized trading sequence. It helps

to find out which of these two trading sequences is helpful to gain maximum surplus, to have maximum trade volume, or to get the prices to converge to the equilibrium level.

4.5. Measuring the Market Performance

There are several measures in literature that are used to measure market performance specifically in experiments and agent-based models. These measures provide varying results for the market performance. It means the performance of the market depends on the measure used to measure the performance. Here we will try to use the market performance measures that are mostly applied in the literature.

In each experiment, after the whole session is completed then the aggregate level performance appraisal will be performed to check the allocative efficiency[22], price variability, coefficient of convergence, and total trade volume. The number of successful trades will highlight how many economic agents were successful in attaining surplus from the trades. On the other hand, a surplus is another profoundly used measure in the literature that shows the gain to buyers/sellers from the trade. Both measures will be compared in the analysis. The competitive market theory predicts market efficiency as the sum of surplus from all the trades in market exchange. We can calculate the market efficiency, E, after measuring the value of maximum theoretical surplus[23], ε. The formula to measure efficiency is given below.

$$E = \frac{\Sigma\,(Vi - Pi) + \Sigma\,(Pi - Ci)}{\varepsilon} * 100 \qquad (4.1)$$

Here V_i is the value of one unit of goods allocated to each buyer and C_i is the cost of producing one unit for each seller. P_i denotes the transaction price of for each transaction and the summation

[22] Here allocative efficiency exhibits the maximum level of surplus the buyer or seller can gain in the experiment/simulation (Davis and Holt, 1993).
[23] Maximum surplus shows the total profit of buyers and sellers from all the trades.

sign is applied only on successful trades as unsuccessful trades do not have a price. The efficiency index, E, is sensitive to the microstructure of the market and must be interpreted accordingly, for instance, if extra-marginal units get traded then it'll have a negative effect on market efficiency.

Another market performance measure taken by Davis and Holt (1993) is the coefficient of convergence, α, which measures the price variability in the market as well as the deviation of transaction prices from competitive equilibrium prices. It's important to measure the gap between the actual market price and the competitive equilibrium price level. It shows in what direction the market is going. It can be measured as the square root of the variance of prices around the theoretical competitive equilibrium level of price and is calculated as,

$$\alpha = \sqrt{\frac{\Sigma_{n=1}^{N}(P_t - \mathrm{P}_e)^2}{N}} \tag{4.2}$$

Where N is the total number of successful transactions in one trading period, P_t is the price at which a transaction takes place and P_e is the competitive equilibrium price level. If all transactions are done at a competitive equilibrium level of prices, then the value of α will be zero showing no difference between transaction price and equilibrium price. The value of α increases with a deviation of mean prices from competitive equilibrium or with an increase in price volatility. It is usually observed in various research that the value of α drops substantially with each trading period showing the convergence of prices towards competitive equilibrium (LiCalzi, Milone and Pellizzari, 2011)[24]. The reason why its value decreases is not analyzed in the literature.

The last measure is the trade volume, which is nothing but the sum of all successful trade in one trading period. In some cases, the averaging trading volume is also considered to compare the

[24] This phenomenon of price convergence is evident in a market following the Marshallian trading sequence.

market performance in the literature. Actual trade volume is compared with the theoretical maximum possible trade that can happen in the market in a trading period. For the market to be efficient, the actual trade volume should be equal to the theoretical trade volume.

All these performance appraisal measures are to be used in evaluating the market performance of all the simulations. The purpose of using the same performance measures as used in studies earlier is to compare the results.

Next section presents the results of all the simulations while applying the methodologies discussed above. The results are presented statistically and graphically also to make them easy to read.

CHAPTER 5

EMPIRICAL RESULTS

This chapter aims to examine the impact of market intervention on efficiency, challenging the common perception that all government interventions result in societal welfare loss. By proposing a novel welfare measure—market employment level—the study emphasizes the societal impact and benefits of employment. It argues that achieving full employment is more critical than merely maximizing surplus. Shifting the focus from profit maximization to full employment, the study suggests that better resource utilization leads to increased overall welfare. Additionally, it evaluates government interventions in the market using data from Pakistan's Household Integrated Economic Survey (HIES), specifically analyzing average wage rate data. The results indicate that, contrary to popular belief, government interventions can sometimes enhance market efficiency, particularly in the presence of market frictions.

Before going into the results and their discussion, it would be convenient to summarize what these results are about. The empirical results of all the simulations are divided into three main parts and each of these is subdivided into two sub-strands, as below.

1. Market performance of ZI agents:
    a. Replication of the ZI market structure offered by Gode and Sunder (1993, 1997, and 2001) while following the Marshallian trading sequence.
    b. Alternative Randomized trading sequence in ZI populated market with varying market demand and supply functions.
2. Market performance when agents can learn about the market:

   a. Duplication of ZI populated market with learning mechanism introduced by Cliff and Bruten (1997) while following Marshallian trading sequence.
   b. Results of alternative Randomized trading sequence in ZI populated market who follows learning rule of Cliff and Bruten.
3. Market performance with new learning rule:
   a. Application of new extracted learning rules (from DeYoung (1993)) in Marshallian trading sequence.
   b. Replication of new learning rules in market mechanism with an alternative trading sequence.

It is important to note here that these six divisions don't imply that only six simulations are executed. It is just the division and within these the simulations are run across various demand and supply functions to ensure that the results are robust. This purpose is attained by implementing three main types of demand and supply functions as follows.

1. Symmetric (with equal but opposite) demand and supply functions
2. Asymmetric (with unequal) demand and supply functions
3. Box-shaped (with relatively constant) demand and supply functions.

Then within these divisions, there is more than one simulation as these demand and supply functions may have a different range of redemption values and costs as compared to other functions.

The results of all these ZI-populated artificial markets are presented here.

5.1. Market Performance of ZI Agents with Alternating Trading Sequences

The performance of ZI agents in an artificial market is subdivided into two parts based on the trading sequence implied in each of these market mechanisms. In the first part, the ZI-populated artificial market is to be built. The section below is dedicated to creating a double auction artificially simulated market where artificial agents can trade with each other.

5.1.1. Market Performance of ZI agents following MS

Initially, it is important to describe the objective we want to attain. The purpose here is to develop a model that explores market efficiency. This includes determining whether efficiency arises from the individual rationality of participants or from the working of an invisible hand in the market. This objective can be attained by looking into the market's performance while controlling the individual rationality of participants. Now the rationality of human participants can be controlled to some extent, but not completely. It is human nature to learn and observe the environment around us. For this reason, it is impossible to control the rationality of human traders in an experiment. The only solution is to rely on artificially generated simulated agents with zero intelligence and examine their behavior in the market. These ZI agents don’t learn but act by as humans make decisions based on the information given to them.

This section is about creating an artificially simulated model with ZI agents to check their market performance in the absence of any kind of learning mechanism. Gode and Sunder (1993) introduce the ZI-populated simulated market that has control over the learning mechanism. Here also, the first step is to come up with a model having the same market microstructure as Gode and Sunder (1993). Here, the purpose is to build the same simulated market following the same microstructure that shall achieve the same results as those of Gode and Sunder (1993). Once the same desired results are achieved, then will be able to bring in modifications in the trading sequence other than the Marshallian sequence, used in literature.

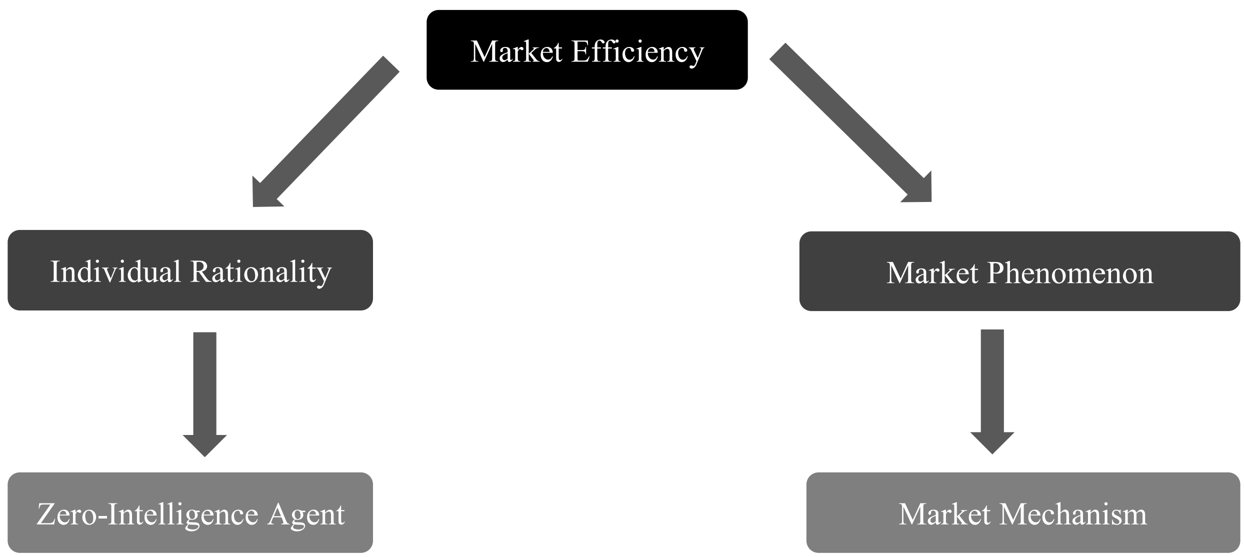

Figure 5.1: Factors Affecting Market Efficiency [Source: Author's own]

As illustrated in the figure above, market efficiency primarily depends on the individual rationality of traders or agents. It also relies on the overall free market forces. These forces enable the market to produce efficient outcomes through an invisible hand mechanism. It is crucial here to first check if these phenomena are the real causes of market efficiency in double auctions or whether it is due to the market itself.

To serve this objective, we bring up here the same market schedules of demand and supply introduced in the ZI-populated market. It is thought that varying demand and supply schedules may have different impacts on market efficiency. It is important to test the market efficiency across types of market schedules. This reason motivates us to bring here all the five types of market schedules used vastly in the literature (William, 1983; Gode and Sunder, 1993 and 2001; Cliff and Bruten, 1997; and others). All these five types of markets are shown in Figure 5.2 below.

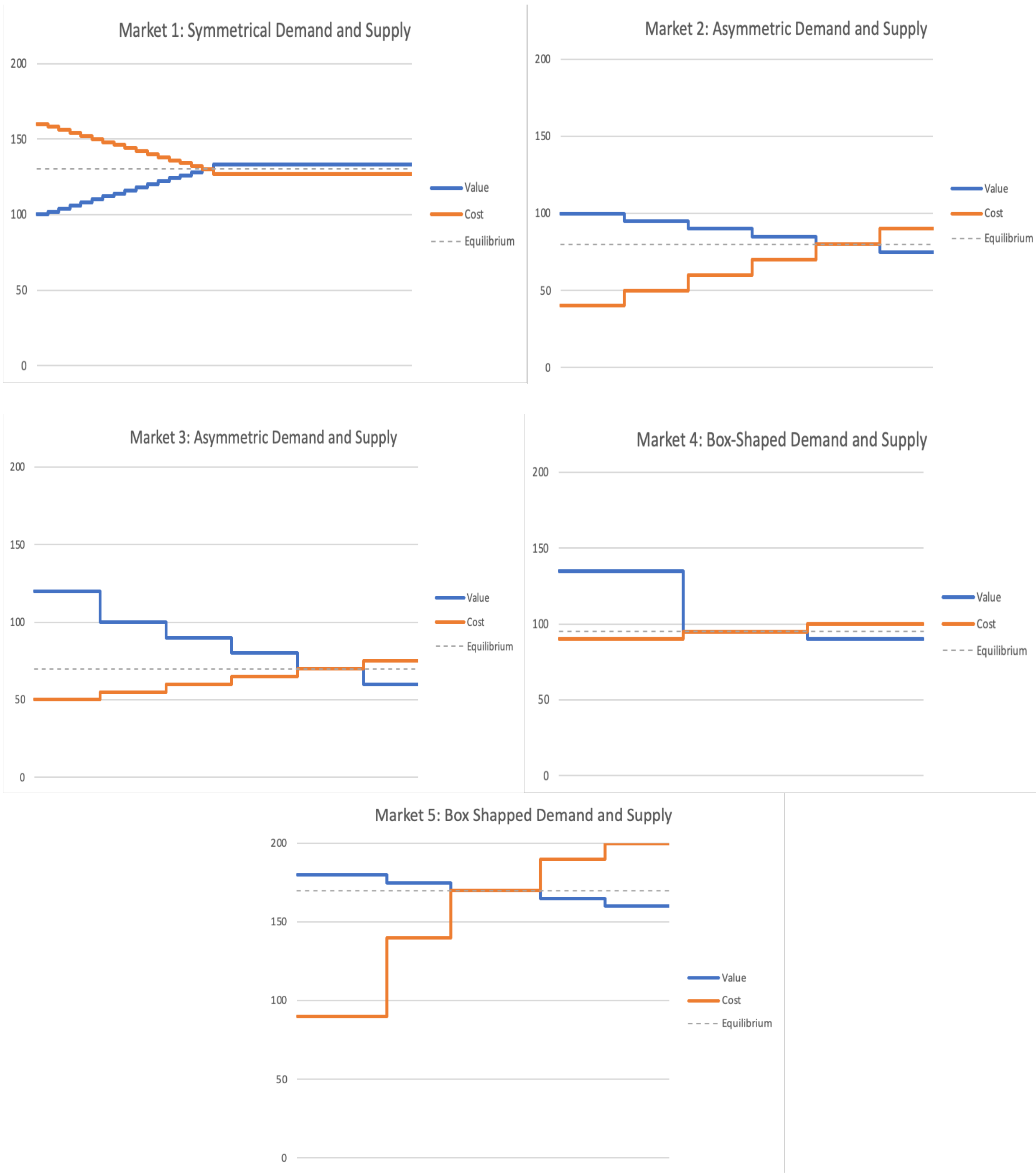

Figure 5.2. Market Demand and Supply Schedules [Source: Gode and Sunder, 1993]

These five demand and supply schedules, used by Gode and Sunder, can be divided into three main classes i.e., symmetric, asymmetric, and box-shaped demand and supply schedules. The first market depicts the symmetric demand and supply schedule as both demand and supply curves mirror one another. Markets 2 & 3 are considered asymmetric demand and supply as in both markets the buyers' values and sellers' costs do not form a market demand and supply just the opposite but the change between values and sellers across traders is different. The last two markets (markets 4 & 5) show the box-shaped demand and supply as the values and costs are allocated in a way that, when drawn on the graph, looks like the shape of box[25].

5.1.2. Market Efficiency: Baseline Model Results

As discussed in the methodology section above, one of the important measures to evaluate market performance is the market efficiency in terms of surplus the market offers. Market efficiency, or allocative efficiency, can be determined as follows. It is the total surplus earned by all the agents in the ZI-populated market divided by the total maximum surplus that could have been earned by all the traders. This maximum surplus is the sum of all consumers' and producers' surplus in the market in one period. To assess if the results of ZI populated DA market provides the same results as of Gode and Sunder (1993), the same allocative efficiency measure is used as a tool to evaluate performance. This comparison is served in Figure 5.3 below, showing how market allocative efficiency has changed over the periods across different markets. All five types of markets are simulated to get an idea of how the allocative efficiency evolves and fluctuates.

Before going into the result of these simulations, it is worth mentioning what are the outcomes of Gode and Sunder (1993) simulations with ZI agents. In the case of symmetric demand and supply

[25] Here the asymmetric and box-shaped demand and supply curves are categorized differently although box-shaped demand and supply is also one type of asymmetric demand and supply schedule.

schedule (market 1, Figure 5.3), initially the market efficiency has been around 98 percent but with each trading period the efficiency decreases. Still, an overall efficiency remains within the range of 96 and 98 percent. In case of asymmetric markets (markets 2 and 3, figure 5.3), the allocative efficiency has been relatively high when compared with symmetric demand and supply markets.

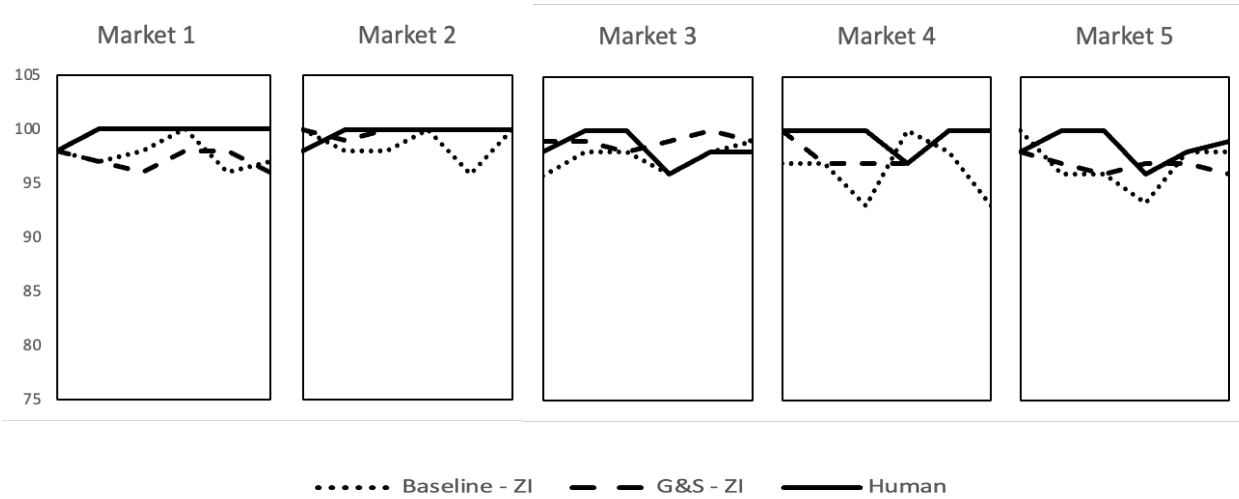

Figure 5.3: Allocative Efficiency Across Markets with Varying S&D Schedules

[Source: Author's own]

The results of our DA market simulation populated with ZI agents deliver approximately the same allocative efficiency except that it differs across varying demand and supply schedules. Our simulation results resemble those of Gode and Sunder (1993). The efficiency remains within the range of almost 95 to 100 percent across all periods. This consistency is observed in all five types of market demand and supply schedules (see Figure 5.3). The only difference is regarding efficiency across symmetric and asymmetric demand and supply schedules. In Gode and Sunder (1993), the symmetric demand and supply schedules are relatively less efficient in terms of providing surplus while the opposite is the case in simulations done here.

Table 5.1: Mean Efficiency of Markets (Baseline Model)[26] [Source: Author's own]

Market	Market 1	Market 2	Market 3	Market 4	Market 5
G&S – ZI Agents	97.1	99.9	99.2	99.0	97.0
Baseline – ZI Agents	98.0	99.0	97.0	96.0	98.0
Human Trader	90.2	99.7	98.0	100.0	99.1

The allocative efficiency in artificially simulated markets is relatively low if compared with human-populated markets, especially in symmetric demand and supply scheduled markets (90.2 percent VS 98.0 percent respectively). This is because in markets with human traders, there is a low dispersion of transaction prices from the mean value as compared to an artificially simulated market. This dispersion causes a difference between the shout prices of buyers and sellers and the transaction prices. Higher efficiency in the zero-intelligence populated market would be the result of this wider difference between the shout and transaction prices randomly selected by the agents. But in all the asymmetric markets (markets 2, 3, 4 & 5) the efficiency of the ZI-populated market lies near to the human-populated DA market.

For further comparison, the mean efficiency for all five types of markets is displayed in the table below. For comparison, the allocative efficiency of Gode and Sunder's (1993) markets is also fetched here. The period-wise mean efficiency of markets for symmetric, asymmetric, and box-

[26] The only difference exposed in these results is a bit more (only 1 percent) higher allocative efficiency in symmetric demand and supply schedules in our simulation as compared to the simulation of Gode and Sunder (1993), which is insignificant. The same is the case for asymmetric demand and supply schedule. But the simulation results of box-shaped demand and supply schedules conform with that of Gode and Sunder (1993).

shaped demand and supply exhibits a surplus that is in proximity (with a difference of not more than 1 percent across varying market schedules).

5.1.2.1. Profit Distribution: Baseline Model Results

Another measure to appraise the model's performance is the root mean square difference. This measures the difference between the actual surplus earned by ZI agents and the equilibrium profit distribution of individual agents. The greater value of the root mean square tells that the actual profit distribution is away from the theoretical market equilibrium. A market with overall higher profit across the trades will also have a higher root mean square value. The Opposite is the case for the market having low distributed profit across the agents.

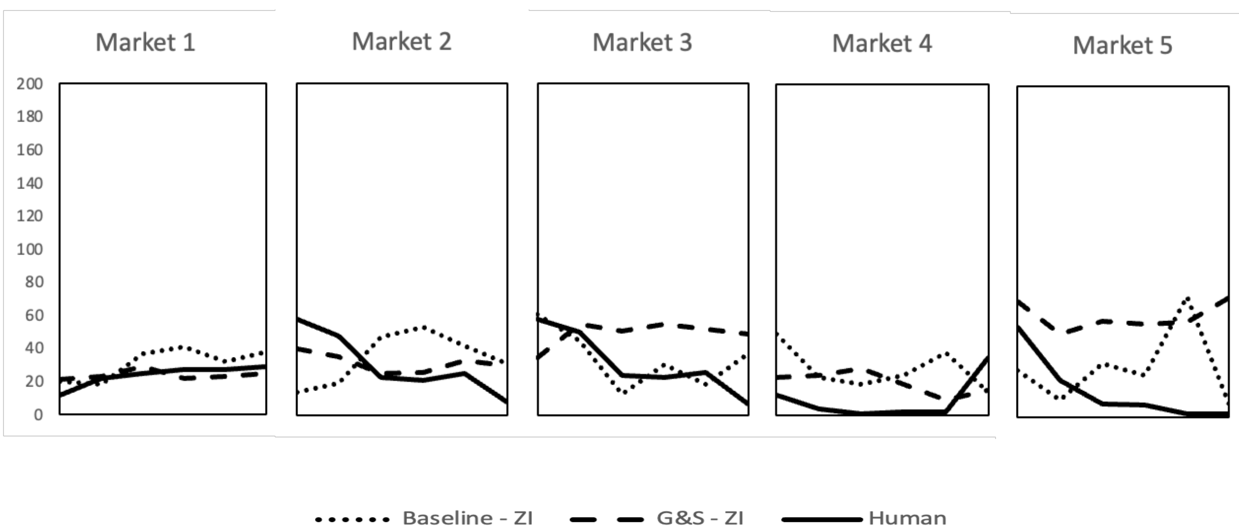

Figure 5.4: Average of Root Mean Squared Difference [Source: Author's own]

If comparing the root mean square of all these five markets with G&S, all markets except market-1 have almost the same range. The root mean square value in the case of market-1 is a bit higher showing relatively more fluctuation. The same results are seen in terms of the allocative efficiency of the market as our simulated market is comparably more efficient by providing a higher level of surplus to traders. This is because higher market efficiency comes from a higher level of surplus attained by the agents. This higher surplus can be achieved when there is a high difference between the shout price and the transaction price. A lower root mean square, along with higher allocative efficiency, indicates that the transaction price is relatively closer to the competitive equilibrium price. This results in a lower root mean square value. However, the difference between the transaction price and the shout prices of buyers and sellers is relatively higher. This leads to higher allocative efficiency. This combination of lower root mean square value and higher allocative efficiency is observed in all markets except market-1 (where both are higher relative to G&S).

The combination of lower root mean square values and higher allocative efficiency across most markets signifies a trend. It indicates that transaction prices tend to align more closely with competitive equilibrium prices. This alignment results in lower price volatility. However, despite this alignment, there remains a notable discrepancy between transaction prices and shout prices. This disparity contributes to higher allocative efficiency, as it indicates a greater potential for surplus generation among market participants.

Table 5.2: Average Root Mean Square Difference in Surplus (Baseline Model)

Study	**Market 1**	**Market 2**	**Market 3**	**Market 4**	**Market 5**
G&S – ZI Agents	19.07	28.53	49.81	15.9	60.47
Baseline – ZI Agents	27.24	29.16	34.3	27.8	29.16
Human Traders	30.69	18.67	28.74	8.23	15.37

[Source: Author’s own]

When comparing the results of the ZI-populated market with those of human-populated traders, a difference is observed. Human traders have a relatively lower root mean square value across all the asymmetric and box-shaped demand and supply scheduled markets. The exception is the symmetric market. But in the case of ZI traders, an average value of root mean square difference is found to be relatively consistent across all the markets, as presented in Table 5.2 and Figure 5.4. In general, the difference of transaction prices from the competitive equilibrium level of prices is relatively higher for a simulated market populated with zero intelligence traders having no learning mechanism as compared to human traders. These highlight the importance of understanding how different market mechanisms influence price dynamics and resource allocation, ultimately shaping the overall efficiency and performance of the market.

In addition to these measures of allocative efficiency and profit distribution across the periods, another important measure is the coefficient of convergence which emphasizes the level of variability in transaction prices.

5.1.2.2.Coefficient of Convergence: Baseline Model

The coefficient of convergence is a measure that explains the pricing behavior in the market. Two types of variations it explicates: one is regarding the variability of transaction prices across the trades and the second is about the deviation of transaction prices from the competitive equilibrium level[27]. Note that both channels are different from one another. The price variability measures only the fluctuations in prices over the trades whereas the deviation examines how far the prices go when compared with competitive equilibrium price level[28].

The value of the coefficient of convergence is unbounded from the higher range. Its values increase with the volatility of prices. Additionally, it increases with the deviation of the mean price from the competitive equilibrium price level.

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[27] It is to note here that this measure of coefficient of variation is not used by Gode and Sunder (1993) but instead, they used root mean square. But we also bring it up to explain how the transaction prices fluctuate over the trades.
[28] It is mentioned in the methodology section how the coefficient of convergence is measured for each period.

In the case of the human-populated DA market, the value of the convergence coefficient decreases over time. This decrease occurs as traders learn about market dynamics (William, 1980). It indicates that, over time, price volatility and the fluctuation of transaction prices from the equilibrium price level decline. A decrease in the distance of transaction prices from the competitive equilibrium price level means a decrease in surplus on one hand but also a decline in price variation.

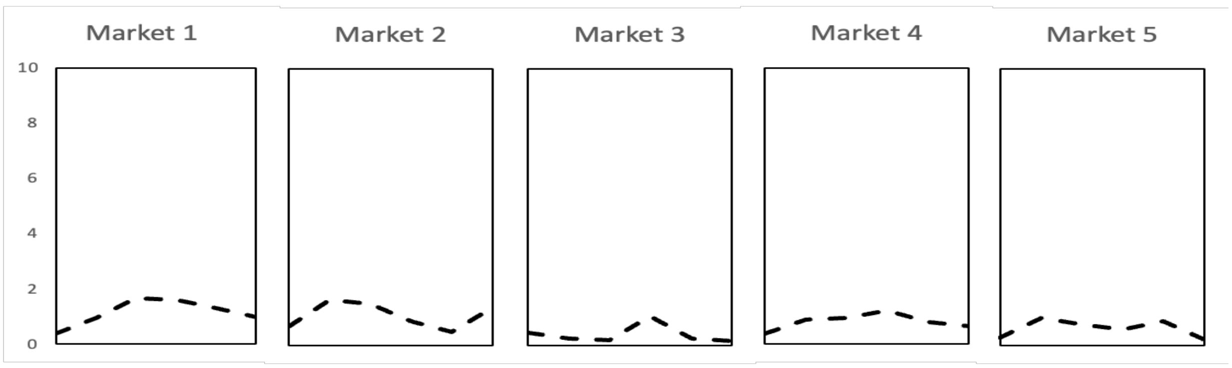

Figure 5.5: Coefficient of Convergence: Baseline Model [Source: Author's own]

In an artificially simulated market populated with ZI agents, the coefficient of convergence should not be decreased as the agents don't possess any rationality and don't have any learning mechanism. As shown in Figure 5.5 above, the coefficient of variation is almost the same across the market except for the symmetric demand and supply market. This can be due to the high range of demand and supply schedules in this market when compared with other markets.

The coefficient of convergence for ZI agents is quite high compared with human traders, which shows higher variability of prices in the case of simulations. Another difference between simulation results in ZI populated market in comparison to human-populated market is the declining trend of coefficient value in the case of human traders.

Table 5.3: Coefficient of Convergence: Baseline Model

Coefficient of Convergence	Market 1	Market 2	Market 3	Market 4	Market 5
Baseline – ZI Agents	1.15	1.10	0.38	0.81	0.71

[Source: Author's own]

This declining trend in the coefficient of convergence for ZI agents, even without rationality and the availability of any learning mechanism, is because of the way how the market mechanism is organized and how the transactions take place. For this reason, it is important here to study the role of the market mechanism separately while controlling all the other elements in simulations. The next section is dedicated to discussing this matter in detail.

5.1.2.3.Trade Volume Efficiency: Baseline Model

Trade volume or quantity of units traded in a period is also an important determinant of the market. Allocative efficiency measures how much surplus the market can offer to traders. Trade volume signifies the extent of demand and supply that is met by agents. In other words, it shows how many agents successfully made transactions and how many had unmet demand. The market may offer a higher surplus but a low volume of trade that leads to higher allocative efficiency but lower trade efficiency. This section attempts to highlight the trade volume efficiency of an artificially simulated baseline market, developed in line with G&S.

Here trade volume efficiency is measured by dividing the actual number of trades that are happening in one period as a percentage of the maximum possible trades that can happen in that specific period. Maximum possible trade is also known as competitive trade volume that is already known to the experimenter. It is calculated by first arranging the redemption values of all the buyers in descending order and the costs of all the sellers in ascending order. First, it is determined how many trades can go through. This starts with the buyer of the highest redemption value trading with the seller of the lowest cost. Next, the second highest redemption value buyer trades with the second lowest cost seller. This process continues in the same manner for the remaining buyers and sellers. If the actual trades that happen in the simulation are just equal to the maximum possible number of trades or competitive equilibrium trade volume, then the market possesses 100 percent trade volume efficiency.

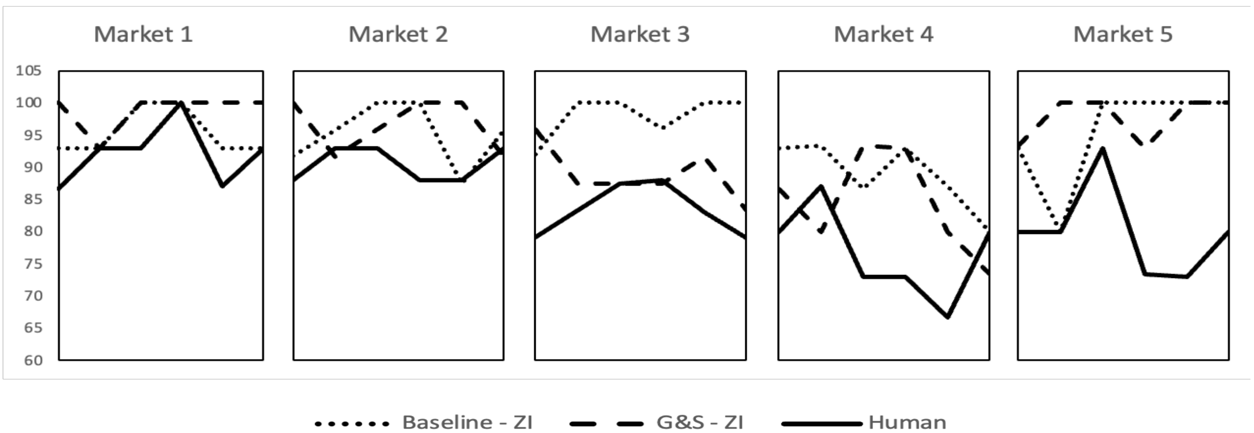

Figure 5.6: Trade Volume Efficiency: Baseline Model [Source: Author's own]

As shown in Figure 5.6 above, the trade volume efficiency remains very high in market-1 (with a symmetric demand and supply schedule) if compared with other markets where it keeps fluctuating over the periods. For the baseline model, the trade volume efficiency in the case of box-shaped demand and supply schedule is relatively lower, as is for G&S. The number of successful trades has been higher for artificially simulated markets than human-populated markets because of the risk-averse behaviour of traders in the later. It is worth noticing here that the highest volume efficiency doesn't always ensure the highest allocative efficiency. The market with the highest trade volume can have relatively low allocative surplus efficiency. The reason behind this can be the shout pattern that ultimately determines the traders' surplus and overall allocative efficiency of the market. For instance, if the shout prices are very close to the redemption values of the buyers or the costs of the sellers then the extra-marginal traders have relatively higher chances to get into successful trade. The more the extra-marginal traders got into the trade, the less the overall surplus in the market. Although the volume efficiency can be high when more extra-marginal traders get into the trade, it leads to lower surplus efficiency.

Table 5.4: Trade Volume Efficiency: Comparison Across Markets

Markets	**Market 1**	**Market 2**	**Market 3**	**Market 4**	**Market 5**
G&S - ZI Agents	99.7	97	89	84	98
Baseline Model - ZI Agents	95	95	98	89	96
Human Traders	92	91	83	77	80

[Source: Author's own]

Human traders' markets have relatively less volume efficiency than the artificially simulated market. It is because of the nature of artificial markets as the market mechanism is organized in a way that ensures a higher possibility of getting into more trades than the human-populated DA market. As described above, even with a low number of trades in a human-populated market, the allocative efficiency is higher than that of the ZI-populated simulated markets. The reason is the higher pursuit of profits and risk-averse behavior of traders that is not there is an artificial market[29].

5.1.3. Market Performance of ZI Agents with Randomized Trading Sequence

The last section helps to develop a ZI-populated DA market that provides the same results as G&S. All the parameters—allocative efficiency, root mean square difference, coefficient of convergence, and trade volume—provide results in line with earlier results of the ZI-populated market. However,

[29] In the artificially simulated market, the agents are shouting the pricing randomly without any rationale behind it. So, even if they get into a greater number of trades the overall surplus from trade is still less than the human-populated market with profit-maximizing traders.

these results differ from those observed in the human-populated DA market. This baseline model can now be used to test various variations in the DA market, whether to examine the market mechanism, demand and supply schedules, or the importance of rationality/learning in the DA market.

In this section, the focus is on examining the importance of market structure. The market structure means how the market is structured to let the trades go through among the agents or what the rules that the agents follow to trade with each other. Market structure is important to assess how the market efficiency is going to change due to changes in the rules of trading among the agents. Here the question arises about the practicality and importance of these trading rules. Trading rules possess a central position when focusing on market efficiency. It is important not only in terms of the allocative efficiency of the market but also in terms of price convergence and trade volume efficiency.

The purpose of testing an artificially simulated market is to analyze its efficiency. It seeks to determine if markets, by default, always lead to outcomes predicted by competitive equilibrium theory. Alternatively, it examines whether specific market details play a key role in achieving these results. As per the literature, markets always lead to the same conclusion as illustrated by theory. But all these initial simulations use the Marshallian sequence of trading. Here, the market efficiency is to be tested by introducing an alternative sequence of trading among the agents. This alternative trade sequence is illustrated in the methodology section, named a Randomized trading sequence.

The principal difference between the Marshallian sequence and the Randomized trading sequence is how agents are selected to shout the prices and trade with one another. Concisely, the Marshallian sequence involves selecting agents in an artificially simulated market. It picks the buyer with the highest bid price from all buyers who have made shouts. It also selects the seller with the lowest ask price from all sellers who have made shouts in the open market. It is because of this specific trading sequence that the market provides a high surplus and leads to allocative efficiency close to the human-populated DA market. It is important to note here that in a ZI-populated market, agents don't possess any intelligence, and learning mechanism, but still, they provide an efficient level of outcome. The purpose here is to test whether the market will still provide an efficient outcome if the trading sequence is changed from Marshallian to Randomized.

It is illustrated in Figure 5.7 that the outcome of the market mechanism is contingent to the type of trading sequence used in the trading process. When the Marshallian sequence is used as the trading mechanism between the agents then the double auction market leads to the results very close to the predictions of competitive equilibrium theory. Now, a new trading sequence is being introduced: the randomized trading sequence. The attempt is to analyze if market efficiency is an intrinsic property of the DA market. Alternatively, the analysis seeks to determine if specific trading sequences cause the market to lead to competitive outcomes. The details regarding the randomized trading sequence are given in the research methodology section. The main difference between Marshallian trading and Randomized trading sequence is the extent of randomness allowed to agents in selecting their trading partners. In the Marshallian trading sequence, once the agents shout their respective bid or ask prices, they are selected randomly and the buyer with the highest redemption value trades with the lowest ask price seller. Whereas, in a randomized trading sequence the agents are not only selected randomly at the start of the trading process but once they shout their prices then they select their trading partners randomly. This difference between these two trading sequences ensures the randomness in the market mechanism in the Randomized trading sequence.

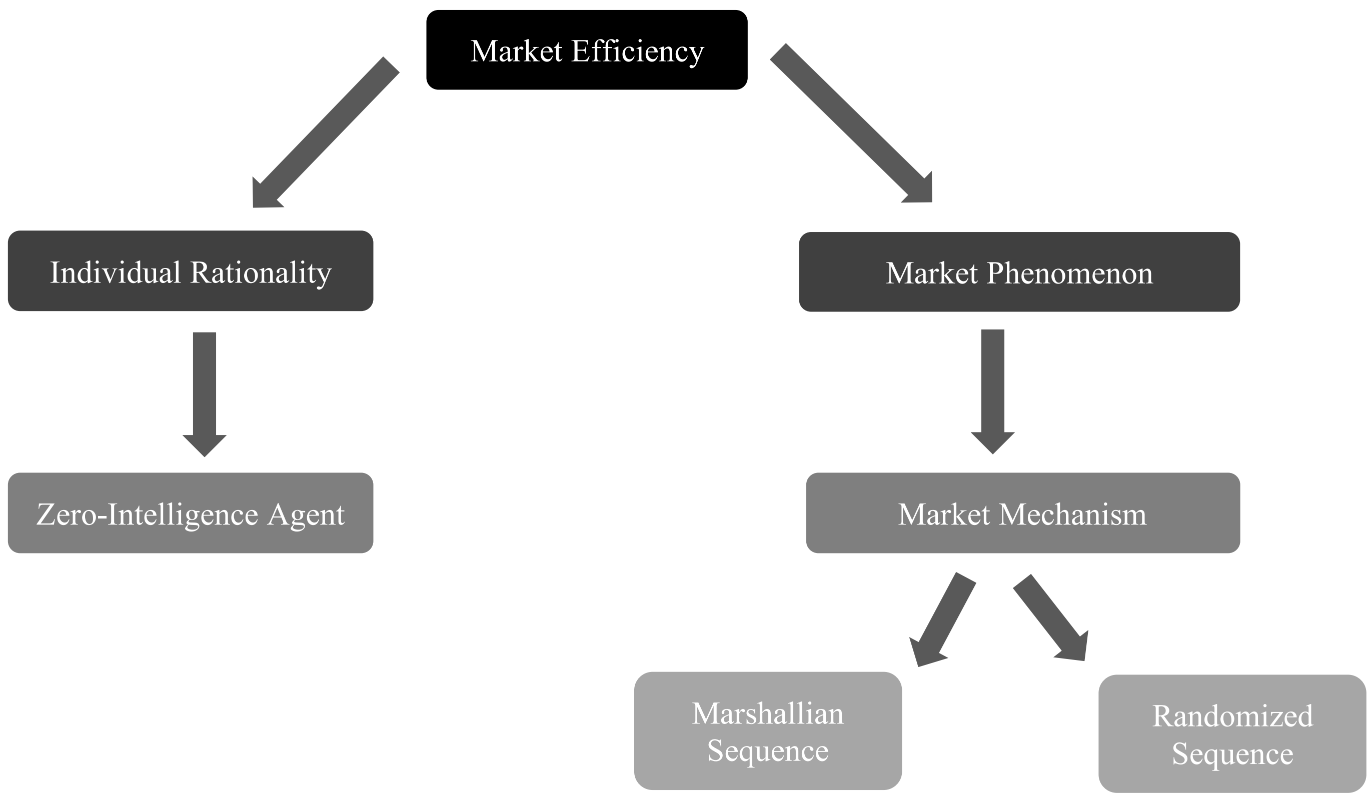

Figure 5.7: Market mechanism with alternative trading sequences [Source: Author's own]

Now to examine if the market still leads to the outcome as predicted by competitive economic theory, an alternative to the Marshallian trading sequence is applied in an artificially simulated double auction market. For this purpose, as a first step, five same market types are used as in the previous section i.e., one symmetric demand and supply market, two asymmetric demand and supply markets, and two box-shaped demand and supply markets. Like before, again the same market efficiency measures are brought up here including allocative efficiency, price convergence, and trade volume efficiency.

5.1.3.1.Market Efficiency – Randomized Trading Sequence

The market efficiency is measured by allocative efficiency – that is by measuring the total surplus gained by all the traders in the market as a percentage of the total maximum surplus that can be gained as per competitive equilibrium theory. This purpose is served by testing again all the five markets of G&S illustrated in the last section.

The allocative efficiency of all five markets is presented in Figure 5.8 below. Allocative efficiency varies significantly across the market trading sequences i.e., Marshallian and Randomized trading sequences. The symmetric market microstructure has relatively higher allocative efficiency if compared with asymmetric and box-shaped market demand and schedules.

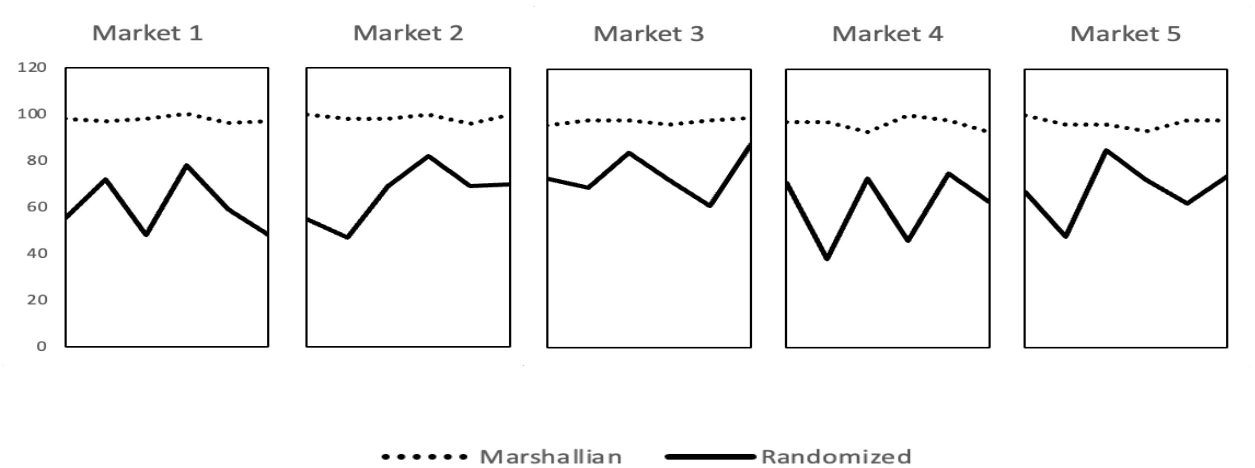

Figure 5.8: Period-wise allocative efficiency for different market trading sequences

[Source: Author's own]

An average of allocative efficiency for both types of trading sequences is available in Table 4.5. The market with a symmetric demand and supply schedule has the highest allocative efficiency on average for all the periods. There is no huge difference between the allocative efficiencies of asymmetric and box-shaped demand and supply.

Table 5.5: Average allocative efficiency across the markets

Trading Sequence	Market 1	Market 2	Market 3	Market 4	Market 5
Marshallian – ZI Agents	98	99	97	96	97
Randomized – ZI Agents	60	79	77	61	68

[Source: Author's own]

Low allocative efficiency in randomized trading sequence in relationship to the Marshallian trading sequence, proves that the trading sequence of the market plays a vital role in achieving allocative efficiency. It means the markets are not efficient to always lead to the best outcome as illustrated by competitive equilibrium theory, but the outcome depends on the details of the microstructure chosen in the simulations. It is important here to look at the other measures of market efficiency as how they behave in Randomized trading sequences.

5.1.3.2.Trading Volume Efficiency – Randomized Trading Sequence

Literature mainly focuses on the allocative efficiency of markets that comes from the combined surplus of all the buyers and sellers who successfully trade in the market. This measure is important to describe as the focus has been on measuring the overall profit the markets can offer to the traders. As competitive equilibrium theory also possesses a crucial condition for the markets to be efficient, i.e., profit maximization, allocative efficiency is usually considered an inevitable variable in measuring market performance.

Similarly, if the focus of the market is to meet the needs of the maximum number of traders, then we shall investigate the number of trades happening across different types of markets. This purpose is served by looking into the trade volume efficiency of the DA market.

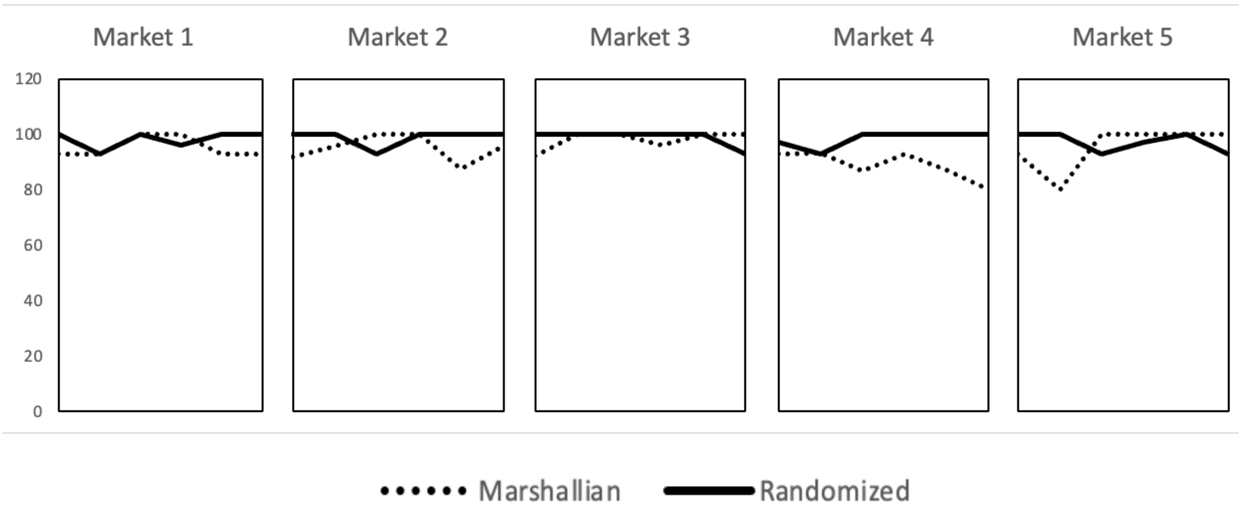

Figure 5.9: Trade volume efficiency for Marshallian vs. Randomized trading sequences
[Source: Author's own]

Overall results of trade volume efficiency are in line with the trade volume efficiency of the Marshallian trading sequence as both measures show very high trade volume efficiency. Trade volume efficiency is a bit higher for Randomized trading than the Marshallian sequence as higher chances of trade are available to the agents. It shows that the Randomized trading sequence is important to provide the desired results for trade volume efficiency. So, the market efficiency in terms of trade volume is not independent of the market microstructure.

Table 5.6: Average trade volume efficiency across the markets

Trading Sequence	Market 1	Market 2	Market 3	Market 4	Market 5
Marshallian – ZI Agents	95	95	98	89	96
Randomized – ZI Agents	98	99	99	98	97

[Source: Author's own]

For trade volume efficiency, all markets with five different types of demand and supply schedules have trade volume efficiency close to each other. Both measures (allocative efficiency and volume efficiency) shed light on the importance of micro details of the market including how the market is set up, what rules define the trading process, how the traders select the shout prices, what is the demand and supply schedules, etc. Confirmation of high levels of trade volume and low allocative efficiency proves that the market by itself is not enough to always lead to efficient outcomes, but the outcome depends on how the market is set up. In addition, to allocative and trading efficiencies it is imperative to investigate the price behavior along the trades i.e., if the trade price converges toward the equilibrium over the trades or not. The section below provides the details on price convergence in the DA market with a Randomized trading sequence.

5.1.3.3. Price Convergence – Randomized Trading Sequence

To get an overall view of the behavior of trade prices a comparison is drawn between the Marshallian and Randomized trading sequences. The movement of trading prices across the periods shows if the transaction prices are becoming closer to the equilibrium price level or going away from it. The gap between the transaction price and the competitive equilibrium prices is surplus from trade[30]. Decreasing the gap between the actual transaction price and the theoretical equilibrium price ensures a decreasing surplus of trades. Another way to demonstrate this same phenomenon of price convergence is by looking into the bid-ask shout spread of successful agents in the market. If the gap between bid and ask shouts decreases over the trades, then it leads to a lower difference between the transaction prices and the shout price which ultimately results in a lower trade surplus.

[30] The total surplus from trade is a sum of the surplus of the buyer and the seller. As the transaction price is equal to the shout price of the buyer or the seller who enters the market first, so the trader who enters the market first has a shout price equal to the transaction price. It is because of this reason the trader who enters first gets zero surplus and the total profit from the trade goes to another trader. So, the total surplus from the trade is equal to the surplus of all the traders who enter in the market later. But if the market microstructure is changed and the negotiation happens between the traders then surplus will be divided between traders depending upon their negotiation power.

This explanation of different variants of price convergence exhibits that any of these can be taken to show if the price convergence is happening over the trades or not. If a price convergence happens it ensures that the market is moving towards its theoretical equilibrium. It is the reason that the price convergence behavior of the market is studied over more than more periods. Here the focus is on the transaction prices if they converge toward the theoretical equilibrium price level over the trades across the periods as happens in the human-populated transaction markets.

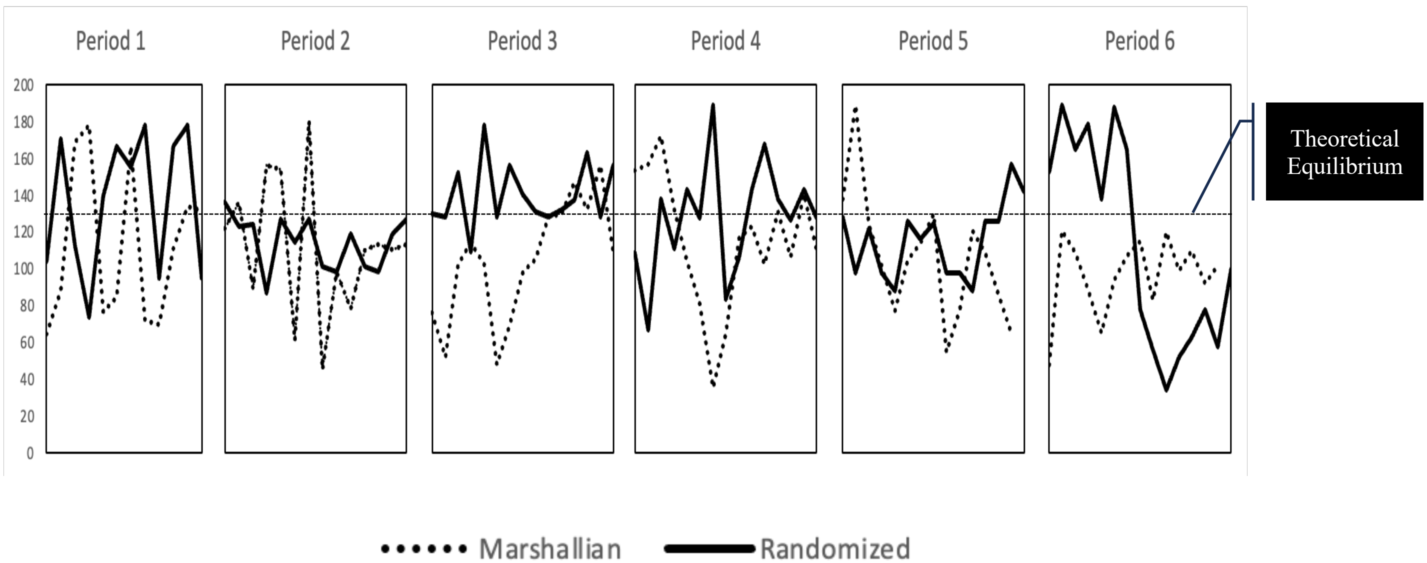

Figure 5.10: Period-wise trading price for symmetric demand and supply schedule
[Source: Author's own]

The transaction prices shown in Figure 5.10 make the comparison between two types of trading sequences in the double auction market. The line crossing over all the periods is the theoretical competitive equilibrium price level. Transaction prices of DA market simulations with Marshallian trading sequence are illustrated in dotted line and for Randomized trading sequence, it is in solid line. The number of trades in the Randomized trading sequence is higher than the total trades in the Marshallian sequence[31].

Here it seems that the bid-ask spread for the Randomized trading sequence is less in comparison to the Marshallian trading sequence. Lower allocative efficiency in the case of a Randomized trading sequence arises from the same reason for not following the Marshallian trading sequence and trading at lower surplus levels. In terms of transaction price convergence towards the equilibrium, it's more than the convergence in the case of the Marshallian trading sequence. In case of randomized trading sequence, the bid-ask spread is lower as compared to the case of Marshallian trading sequence. The reason behind this low bid-ask spread is the randomization in matching the traders instead of matching the traders with extreme bid and ask values. It is the reason that the convergence is also more than it is witnessed in the case of the Marshallian trading sequence.

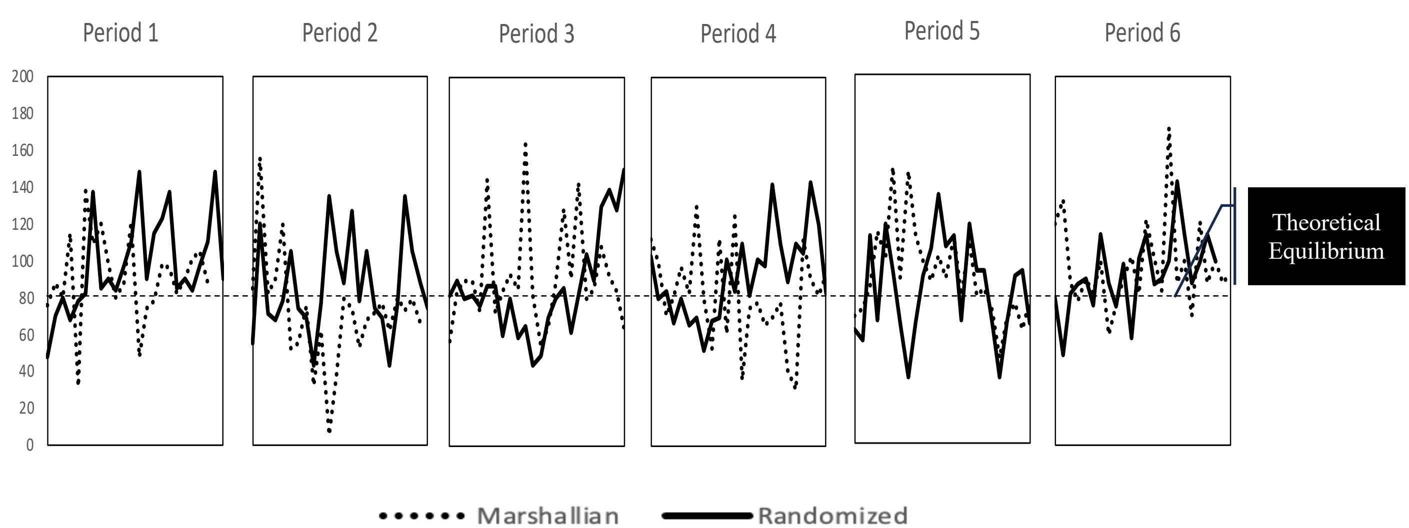

Figure 5.11: Period-wise trading price for asymmetric demand and supply schedule

[Source: Author's own]

[31] The same results are represented through the trade volume efficiency where its value is significantly lower for the Randomized trading sequence when compared with Marshallian trading sequence.

If compare all three types of markets (i.e., markets with symmetric, asymmetric, and box-shaped) demand and supply schedules) the asymmetric and box-shaped markets are found to have relatively less price convergence than the market with symmetric demand and supply schedules. These results are in line with the literature on ZI-populated simulated markets. Among the different trading sequences, the Randomized trading sequences are found to be relatively closer to competitive equilibrium transaction prices than the Marshallian trading sequence. However, this higher convergence level has its tradeoff in terms of allocative efficiency. It is the reason, the market with a Randomized trading sequence has comparably less allocative efficiency than the Marshallian trading sequence.

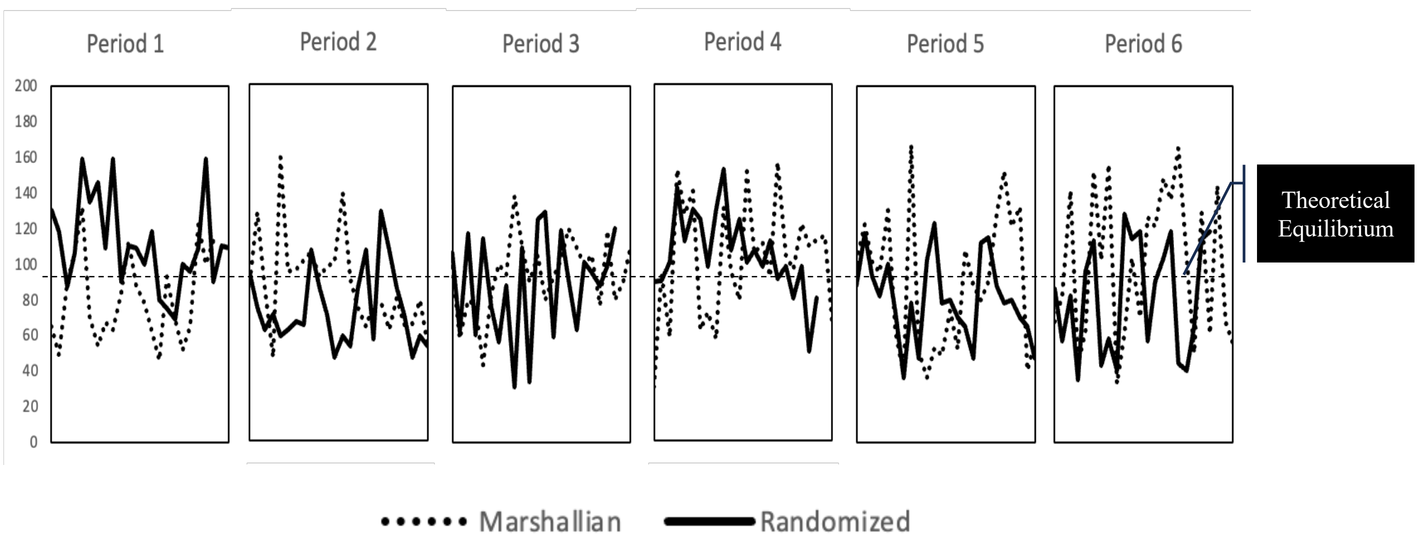

Figure 5.12: Period-wise trading price in box-shaped demand and supply schedule
[Source: Author's own]

These results show that the measure of market efficiency is dependent on the specific details of how the market is set up. By changing these details, the desired results can be attained. So, the market outcome is sensitive to the particularities of the market setting i.e., market microstructure. Although these results raise questions about their general behavior being efficient, they also open new avenues for policymakers. For instance, the results show that one type of trading sequence in the DA market leads to a higher surplus while the other type of trading sequence achieves a higher number of trades. If the policymaker has the objective to achieve a higher level of efficiency in terms of allowing traders to get more profit, then they shall adopt the Marshallian trading sequence. Whereas, when the objective is to make all the trades happen at a price closer to the competitive equilibrium price, then they shall go for the Randomized trading sequence.

While these findings may raise questions about the general efficiency of markets, they also present opportunities for policymakers to tailor interventions effectively. For instance, the analysis reveals that specific trading sequences within the double auction (DA) market can optimize different objectives.

On one hand, adopting the Marshallian trading sequence can lead to higher surplus for traders, thereby promoting profitability and economic welfare. On the other hand, opting for the Randomized trading sequence can result in a higher number of trades occurring at prices closer to competitive equilibrium levels, enhancing market efficiency in terms of price convergence.

Therefore, policymakers faced with the task of promoting market efficiency must carefully weigh these trade-offs and select the appropriate market microstructure to align with their objectives. These results not only shed light on the complex dynamics of market behavior but also offer practical insights that can inform policy decisions aimed at fostering more efficient and effective market outcomes.

5.2.Learning Mechanism in ZI-Populated Market

In the previous section, it discussed how market efficiency depends on the microstructure. Specific details on how the markets are set up, are important to consider. The competitive equilibrium outcome as predicted by competitive market theory is not independent of market microspecification. The markets do not always provide efficient results but the results from the market depend on the market microstructure. The results in the first section shed light on this notion. A market populated with ZI agents does not lead to the efficient allocation of resources along with market convergence, but it depends on how the market is structured. For instance, if the market aims to provide a maximum surplus, then the Marshallian trading sequence is suitable. This is true while keeping all other factors constant, such as demand and supply, bid and ask price determination, learning of agents, and constant values and costs over the periods. On the other hand, if the purpose is to get a maximum number of traders and fulfill the demand of as many traders as possible then the most appropriate trading sequence is the Randomized trading sequence. It leads us to conclude that the outcome of the market is sensitive to the details regarding how the market is set to work.

This section focuses on the same theme of the universality of market efficiency irrespective of market microstructure. Like before, the ZI-populated DA market framework is used. The purpose here is to evaluate the market performance in the presence of individual rationality. Here, individual rationality refers specifically to the learning of agents as the market continues. Like controlling the rationality of participants, the ZI agents also don't possess any learning phenomenon. The initial results of ZI-populated simulated markets show that rationality and learning are not required for the market to be efficient. Even after controlling these, the DA market provides allocative efficiency close to experiments with human traders.

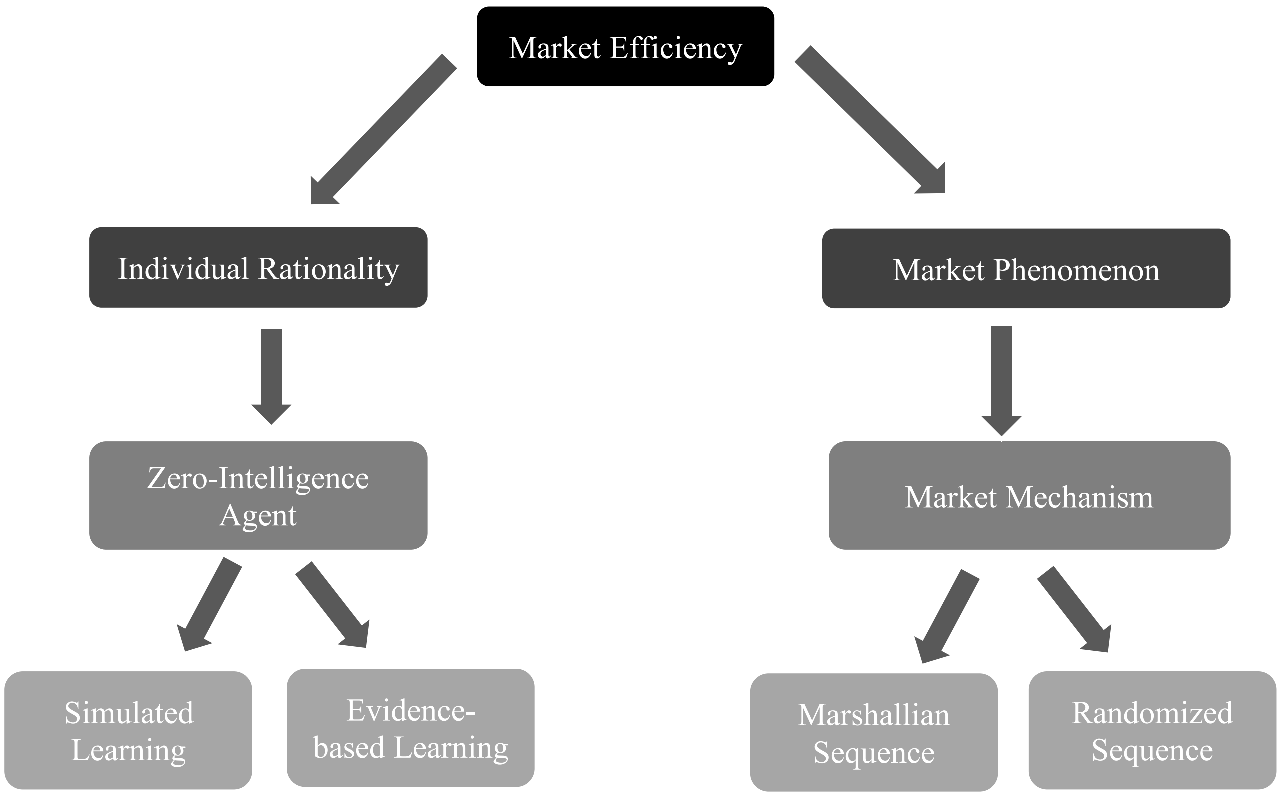

Figure 5.13: Market mechanism with alternative learning mechanisms [Source: Author's own]

As the results of the ZI-populated market regarding market efficiency are questioned in the last section so, these same results shall also be assessed for the learning of agents. The first notable work in this line is done by Cliff and Bruten (1997). They incorporate a learning mechanism in ZI agents. Their work shows how market efficiency increases when agents are allowed to learn about the market environment. The market efficiency with learning ZI agents is witnessed to be even more than simple ZI agents with no learning mechanism. It leads to the conclusion that in artificially simulated markets, the learning mechanism has a significant impact on the outcome by enhancing the market efficiency of agents.

For this reason, it is worth an effort to dig into the effect of learning on the performance of ZI agents. This process is illustrated in Figure 5.13 where the rationality of ZI agents can be subdivided into two strands: one is the efficiency coming from the simulated learning rules while the other comes from the learning rules extracted from human experiments in the DA market framework.

After incorporating the learning mechanism in the ZI agents the market performance improves significantly. Cliff and Bruten (1997) named these ZI agents as Zero-Intelligence Plus (ZIP) who can learn about the market process. Here, one of the issues is the kind of learning mechanism embodied in the ZIP agents. The learning mechanism used by Cliff and Bruten (1997) is provided in detail in Section 4, Box 3. Preferably, the learning mechanism of agents should imitate how human traders learn in the market. Otherwise, the experiments with human traders could have been a valuable source of learning rules that could be applied to ZI-populated artificially simulated markets.

But instead of borrowing the learning rules from human experiments, in a ZIP-populated simulated market, the learning rules are just assumed. The focus has been to bring up the learning rules that lead to maximum market efficiency. It is for this reason that the learning mechanism of ZI agents should be revisited by incorporating the learning rules that are extracted from the DA experiment with human traders.

This purpose is served in the following steps.

a. Come up with a ZI model based on learning rules of ZIP agents that provide the same outcome as provided by ZIP traders.
b. The next step is to use extract the learning rules from the experiment with human traders.

c. Now these learning rules, that come from the real human experiment, can be substituted in the ZI-populated simulated market in the first step. The benefit of replacing only the learning rules is to control all the other factors used by Cliff and Bruten (1997) except the learning rules. It will help to investigate the impact of change in the learning mechanism on the performance of ZI agents.

The results for all these three forms of simulations are provided in the coming section. The next section is dedicated to looking into the results of ZI traders with learning mechanisms and how these results are achieved.

5.2.1. ZI-Plus Agents in the DA Market

To imitate the results of Zero-Intelligence Plus agents, the same demand and supply schedules are required to be followed. The demand and supply schedules are illustrated in Figure 5.14 which exhibits symmetric demand and supply as used in market 1 of G&S. Here 200 is the equilibrium price level with an equilibrium quantity of 6 units.

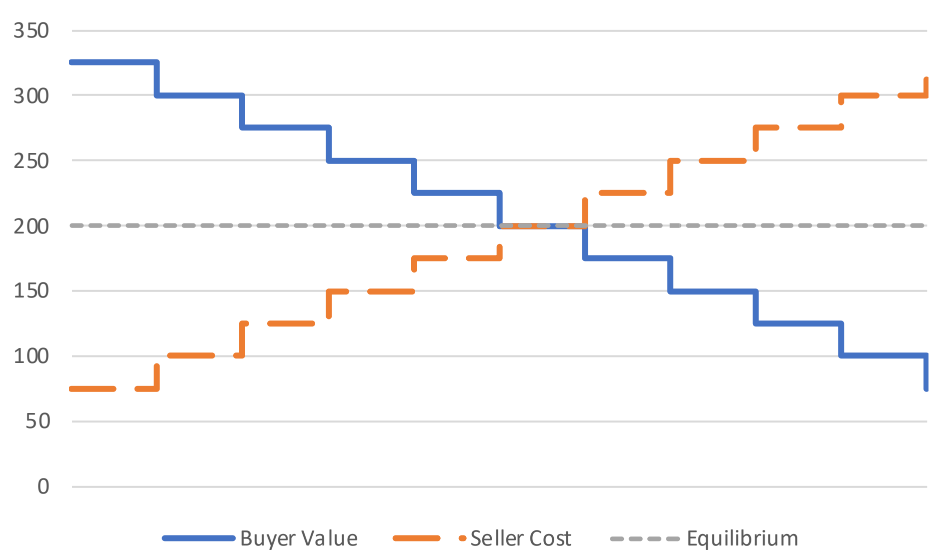

Figure 5.14: Market Demand and Supply Schedule [Source: Cliff and Bruten, 1997]

With the implementation of the ZIP learning rules in the Marshallian sequence, the results from trade across 10 periods are given in Figure 19[32]. The main objective of C&B was to show the price convergence process because of the learning process. Their results just provide period-wise an average transaction price for the same market.

5.2.2. Market Efficiency of ZIP$_H$ Traders with Simulated Learning Mechanism

After applying the same learning rules the results of ZIP$_H$ traders in a Marshallian trading sequence demonstrate the price convergence, as witnessed in C&B[33]. The prices are not only converging towards market equilibrium value but also converging to equilibrium across the periods. These results contrast with earlier results with ZI agents where no price convergence was observed[34]. It shows that the learning mechanism has a significant effect in leading the transaction prices to their theoretical equilibrium value[35].

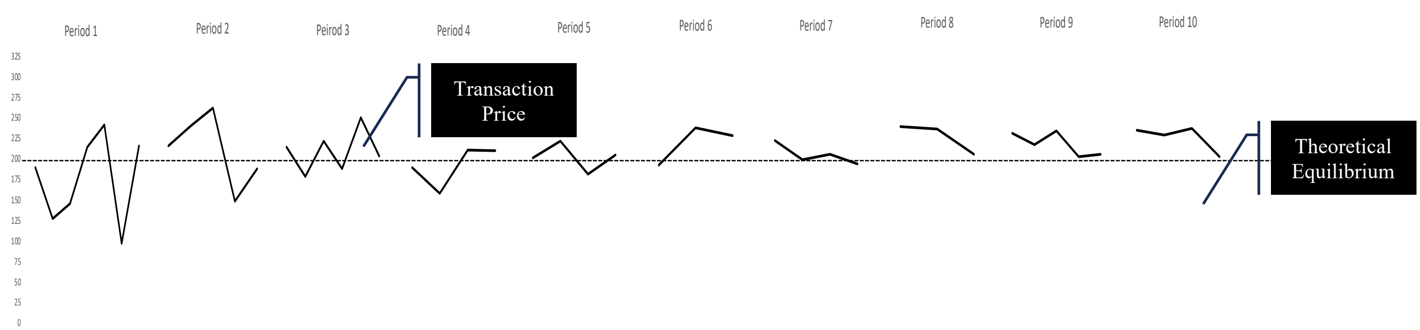

Figure 5.15: Transaction prices with ZIP agents [Source: Author's own]

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[32] The selection of 10 periods is done to imitate the results of Cliff and Bruten (1997).

[33] Here we name the zero-intelligence agents as ZIP$_H$ agents as they possess the learning abilities and these learning rules come from the human-populated experiments.

[34] These learning rules are extracted from the results of human experiments and then applied with ZI-agents in the same market microstructure as it's done for the human traders. After making sure that these rules provide us the same results for the ZI agents as for the human traders then we introduce various alterations of market microstructure i.e., across different supply and demand schedules, for different trading sequences etc. So, the robustness is checked as they provide the same results as for the human traders when applied in the same settings.

[35] As Cliff and Bruten (1997) don't provide analysis on market efficiency, it is why here only the results of price convergence are provided to make sure that these results are in line with the price convergence of ZIP agents.

The convergence of transaction prices over the periods toward the equilibrium price level exhibits the importance of the learning mechanism in the simulated market. The ZI-populated market with no learning couldn't experience price convergence. But it is because of this trait of the market that the prices converge towards equilibrium over the period. When the transaction price happens to be away from the competitive equilibrium price level then it compromises on the effectiveness of the equilibrium price. The equilibrium price is effective in determining the market efficiency and illustrates the market clearing price. Price convergence to equilibrium ensures the market outcome is closer to the theoretical competitive outcome level.

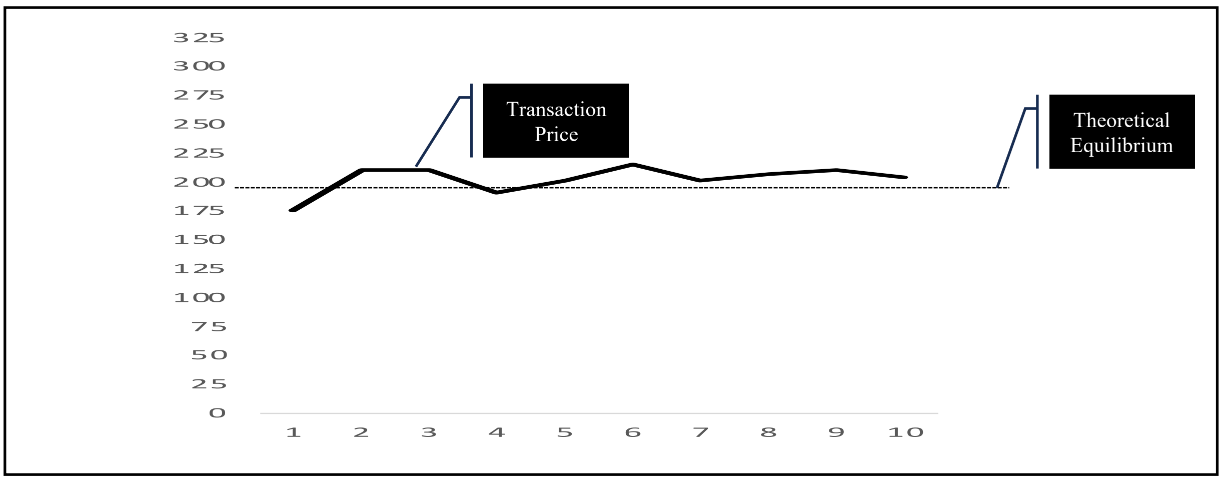

Figure 5.16: Period-wise average transaction price [Source: Author's own]

The average price across the periods also illustrates the same results i.e., the average transaction prices are getting to the theoretical equilibrium price level over the periods. It confirms the markets to be efficient as they may provide efficient outcomes.

Hence, the learning mechanism plays an effective role in moving the prices toward their equilibrium level. Such price convergence is not offered by the simple ZI agents having no rationality and no learning mechanism. These results of C&B are important to demonstrate that the ZIP agents provide a more competitive outcome as compared to ZI agents. The earlier notion of the non-importance of market microstructure posed by ZI agents is negated by getting more efficient results with a learning mechanism. So, the markets need some degree of rationality and learning to be efficient otherwise price convergence is not attainable.

Here the learning rules applied by C&B are assumed to aim to come up with a model that provides more efficiency and price convergence toward competitive equilibrium. These complicated sets of learning rules (stated in Box 3) are far from the way human traders learn in experiments. When learning rules – that affect the market outcome – are not close to reality the results coming from these simulations are to be questioned. This limitation motivates us to revisit these results of C&B by borrowing the rules from the experiments that involve human traders.

In this section, the importance of learning is highlighted by incorporating it into ZI agents. The next question is whether the learning mechanism used by Cliff and Bruten mirrors the actual process of how traders learn during experiments or in real markets. Or, in other words, different results can be obtained by altering the learning framework for the ZI agents.

5.2.3. ZIP Agents with Learning Mechanism of Human Traders with MS: The Baseline Model

The previous section ends by concluding the importance of learning mechanisms in improving the convergence of transaction prices toward competitive equilibrium price levels. This section focuses more on the type of learning used in the ZIP agents along with the Marshallian trading sequence. The emphasis is on introducing the learning rules that are extracted from real experiments with human traders. It will help to analyze the outcome of a simulated market populated with ZIP traders having the learning rules that will come from the experiments instead of assuming rules of our choice.

For this purpose, the study of DeYoung (1993) is used. The reason for using this research is because of the information required about the bid and ask prices of the traders, and each transaction price. Without this information, it is impossible to extract the rules about how the traders learn and how their action is reflected in shout prices over the trades.

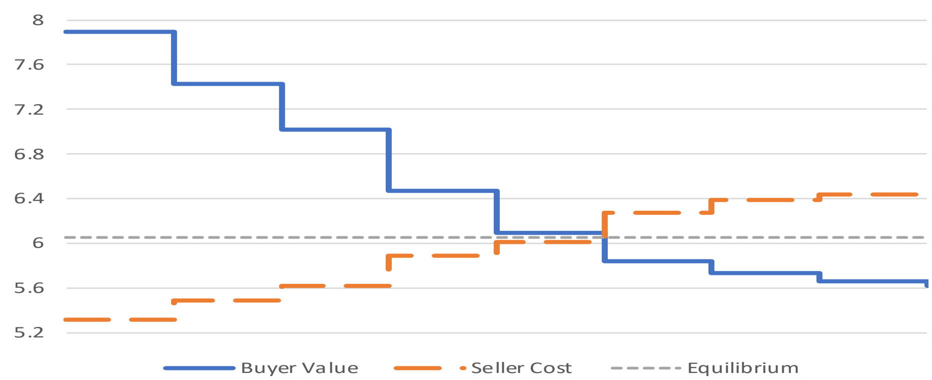

Figure 5.17: Market Demand and Supply Schedules [Source: DeYoung, 1993]

The demand and supply schedules used in DeYoung (1993) are asymmetric, as can be seen in Figure 5.17. The theoretical competitive equilibrium price is 6.05 and the maximum achievable surplus is 6.57 in this market structure.

5.2.3.1.Price Convergence of ZIP Agents with Experiment-Based Learning Rules

Now the purpose of using this market structure is to extract the learning rule from the results of DeYoung (1993) and come up with a ZI-populated simulated market that reaches the same outcome as DeYoung (1993). It will help to ensure the effectiveness of learning rules and the reliability of these rules in the artificially simulated market. Later, this simulated market can be used to check if it provides better results as compared to a market populated by ZI agents with no learning mechanism. As a first step, these learning rules will be applied to a simulated market with the Marshallian trading sequence.

The period-wise transaction prices for DeYoung's market schedule (Figure 5.17) populated with ZIP agents are illustrated in Figure 5.18. The focus here is on examining if the transaction prices converge toward the competitive equilibrium price level.

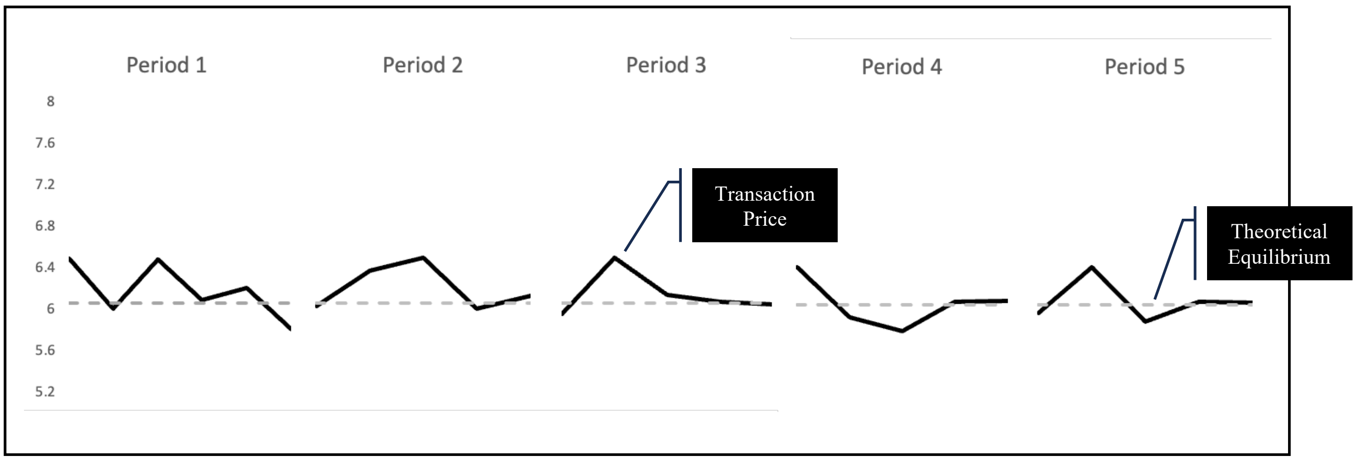

Figure 5.18: Transaction price over the period with ZIP agents with learning mechanism

[Source: Author's own]

An important point to note here is that different parameters are used to check the market efficiency. For instance, earlier, some researchers used the total actual surplus attained and the number of trades between the participants as market efficiency measures (Gode and Sunder, 1993 and 2001). However, in this research, the agents don't possess any rationality or learning mechanism, so they are not expected to provide maximum surplus but are not likely to offer a convergence of transaction prices to the competitive equilibrium. On the contrary, the agent-based simulated markets with learning mechanisms see the market efficiency in terms of the movement of prices toward the equilibrium (Cliff and Bruten, 1997). The reason for taking this efficiency measure is the focus on how agents learn about the market while trading along with the Marshallian sequence.

It is the reason, in simple ZI-populated markets the market efficiency is measured through the allocative efficiency while for ZIP-populated markets the efficiency is captured through the price convergence.

The results of the ZIP-populated simulated market are based on the demand and supply schedules and learning rules extracted from DeYoung (1993). These learning rules are described earlier in the research methodology section (Box 4). Based on these rules the ZIP agents learn how to shout the prices to be successful in getting the desired trade. The results of their learning behavior can be portrayed by the transaction prices. The transaction prices are measured as the shout price of agents who enter the market first. For instance, if the buyer (seller) enters the market first and that specific buyer (seller) has been successful in making the trade with any of the sellers (buyers) who enter the market after the buyer (seller) then the transaction price equals to the shout price of the buyer (seller)[36].

The transaction prices are presented across the periods for the artificially simulated ZIP market having learning rules extracted from human-populated experiments. These results appear in accordance with the results of DeYoung (1993), who involved humans in DA market experiments. The similarity in results artificially simulated market ensures that the market with ZIP agents is calibrated with the human-populated market where humans learn about the market over the trades and across the periods.

[36] Here the transaction prices are recorded and presented for only five periods as done by DeYoung (1993). As the purpose here is to imitate the results of that study but for artificially simulated market populated with ZIP agents so, we have used all the same parameters that the author used for human-populated market.

Transaction prices get closer to the competitive equilibrium price within each period and across the periods. It shows that the ZIP agents learn about the market as time flows and get an idea about the transaction price at which they are more likely to be eligible to trade[37].

5.2.3.2. Allocative Efficiency of ZIP Agents with Experiment-Based Learning Rules

In terms of allocative efficiency, the learning process should be supportive of increasing it. When the agents learn about the market, they shout the price close to the competitive equilibrium price level, and at this price level, only the intra-marginal agents are more likely to trade[38]. The trade between the intra-marginal buyers and sellers leads to higher allocative efficiency. It is why the agents with the learning mechanism should have experienced increasing allocative efficiency over the periods as they learn about the market mechanism.

Table 5.7: Period-wise surplus of ZIP agents over the transactions (In percentage)

	Period 1		**Period 2**		**Period 3**		**Period 4**		**Period 5**	
Agent's Profit	**Buyer**	**Seller**	**Buyer**	**Seller**	**Buyer**	**Seller**	**Buyer**	**Seller**	**Buyer**	**Seller**
Transaction 1	17.9	8.8	23.7	12.8	23.1	14.7	22.9	15.4	22.9	14.8
Transaction 2	19.2	7.8	17.9	15.5	18.6	11.8	18.7	10.7	18.4	10.7
Transaction 3	7.8	6.8	9.3	15.4	12.7	7.8	13.7	8.0	13.5	8.1
Transaction 4	0.2	9.7	7.3	0.0	5.6	0.9	5.6	3.2	5.3	3.1

[37] The price convergence doesn't mean that the market will be allocatively efficient. The reason for lack of efficiency in case of increased price convergence is that the extra-marginal agents may be successful in getting into the transaction with intra-marginal traders. This phenomenon usually keeps theoretical potential intra-marginal traders out from getting into trade and leads to decrease in overall market efficiency.

[38] Intra-marginal agents are the market agents who have a position at the left side of the competitive equilibrium level. Or they are a buyer who has redemption values higher than the competitive equilibrium price and seller who have cost less than the competitive equilibrium price level.

Transaction 5	2.3	3.2	0.3	0.1			0.0	1.5	0.3	1.0
Transaction 6	0.7	0.5								

[Source: Author's own]

The results of the ZIP-populated agent simulated market provide an overview of the impact of learning on allocative efficiency. For the baseline mode, this purpose is served by applying the learning rules (extracted from DeYoung (1993)) on the ZIP agents. The results of allocative efficiency for an artificially simulated market are the sum of an individual surplus of all the buyers and sellers from the trade. To ensure the convergence trend in the transaction prices, the individual surplus must also decrease over the trade.

The individual surplus exhibited in the table above shows that there is a decreasing trend of trade surplus for buyers and sellers in each period. The surplus of buyers is found to be generally higher than the surplus gained by the sellers. The reason for this asymmetric distribution of market surplus is the asymmetric S&D schedule where the redemption values of buyers is relativey far from the equilibrium price level as compared to costs of sellers (Figure 5.17).

Allocative efficiency is then measured from these individual surpluses as the percentage of total possible surplus that the agents can attain from the trades i.e., equal to competitive market surplus. The allocative efficiency over the periods is given in the table below.

Table 5.8: Period-wise allocative efficiency of ZIP traders imitated learning rules (In percentage)

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**
Allocative Efficiency	86.1	97.6	97.8	100	100

[Source: Author's own]

The allocative efficiency increases over the periods as it's 86.1 percent in period 1 and 100 percent in period 5. It shows as time passes, the agents get to know about the market dynamics and start shouting the prices very close to the competitive equilibrium price level. It leads the extra-marginal agents to not trade and only the agents positioned at the left side of competitive equilibrium in the market demand and supply schedules trade with each other and maximize the market surplus. So, when the ZIP_H agents have the learning mechanism mirrored by the learning mechanism of human traders then the transaction price converges toward the theoretical equilibrium price level, and allocative efficiency also increases over the periods.

5.2.3.3. Trade Volume Efficiency of ZIP_H Agents with Human-Based Learning Rules

The third measure of market efficiency is trade volume efficiency which exhibits the number of trades that happen in a period as a percentage of the maximum possible trade that can happen. In a market with demand and supply schedules of Figure 5.17 i.e., borrowed from DeYoung (1993), the trade volume efficiency is quite higher than it is for the ZIP_H agents with no learning.

The theoretical competitive number of trades is 5 in each period for this market. The actual trades in each of these 5 periods are 6, 5, 4, 5, and 5. So, the overall average trade volume efficiency is around 100 percent, which is the maximum the market can offer.

5.2.4. ZIP Agent with Learning Mechanism: Randomized Trading Sequence

Till now, the newly introduced learning model has been implemented in a market with a Marshallian trading sequence. It demonstrates that when learning is introduced to ZIPH agents, their performance improves. They achieve higher market efficiency, as indicated by higher surplus, a greater number of trades, and the convergence of transaction prices. This section now attempts to introduce a learning model in a ZIP_H-populated simulated market that follows the Randomized trading sequence.

The purpose here is to explore the market efficiency when the ZIP_H traders follow human-induced learning rules in a Randomized trading sequence instead of following the Marshallian one. For this purpose, the first step is to introduce three different market demand and supply schedules. These three markets have symmetric, asymmetric, and box-shaped demand and supply schedules are shown below in Market 1, Market 2, and Market 3 as presented in Figure 5.19, 5.20, and 5.21, respectively.

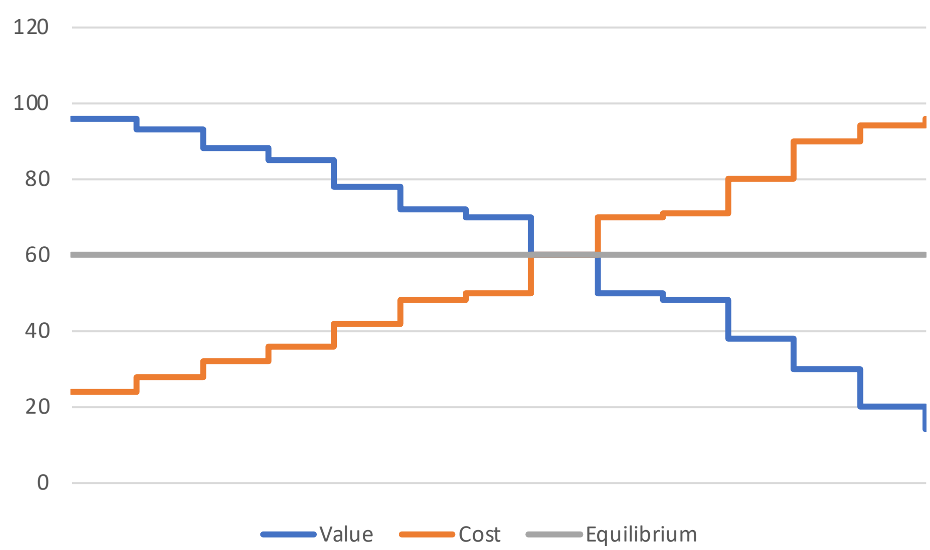

Figure 5.19: Market 1 with symmetric demand and supply schedule
[Source: Isaac and Plott, 2003]

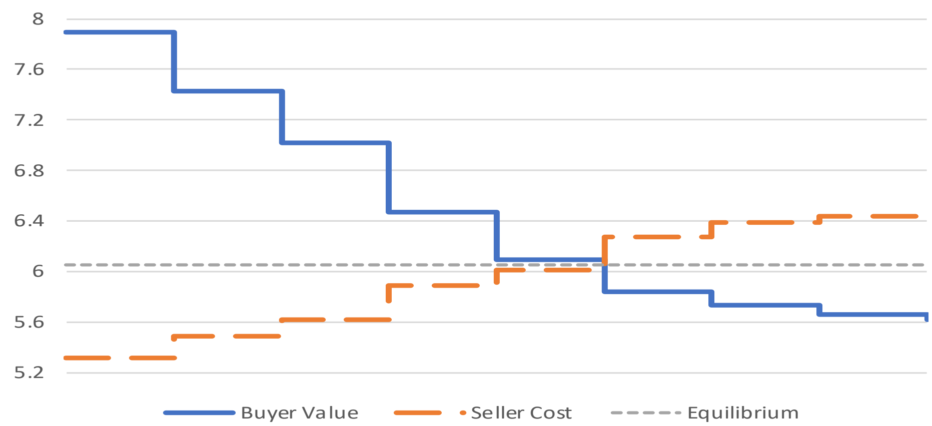

Figure 5.20: Market 2 with asymmetric demand and supply schedule
[Source: Gjerstad, 1997]

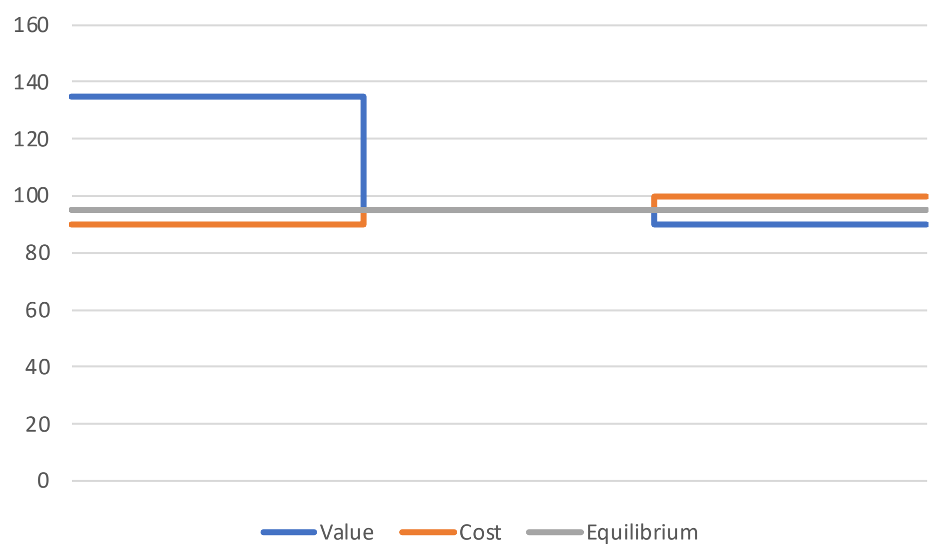

Figure 5.21: Market 3 with box-shaped demand and supply schedule
[Source: Gode and Sunder, 1993]

These three market schedules will ensure that the market efficiency is robust along with alternative demand and supply schedules when the market follows a Randomized trading sequence, and the agents follow human-inspired learning rules. The next section provides the results of market efficiency for ZIP_H agents that follow these three markets demand and supply schedules. As before, the market efficiency is checked through three parameters i.e., convergence of transaction prices, allocative efficiency, and trade volume efficiency of the market.

5.2.4.1. Allocative Efficiency of ZIP_H Traders with Randomized Trading Sequence

The allocative efficiency of the DA market with a randomized trading sequence will ensure whether the learning rules extracted from human market behavior are more efficient or not. Here the ZIP_H agents differ from ZIP agents based on the type of learning rules they follow. The ZIP follows the assumed learning rules whereas the learning mechanism followed by ZIP_H agents is human-inspired learning. The price convergence and allocative efficiency of the market for human experiments are closer to the ZIP traders when the latter follows the Marshallian Path. But here not only the learning mechanism is changed but it is combined with the Randomized trading sequence.

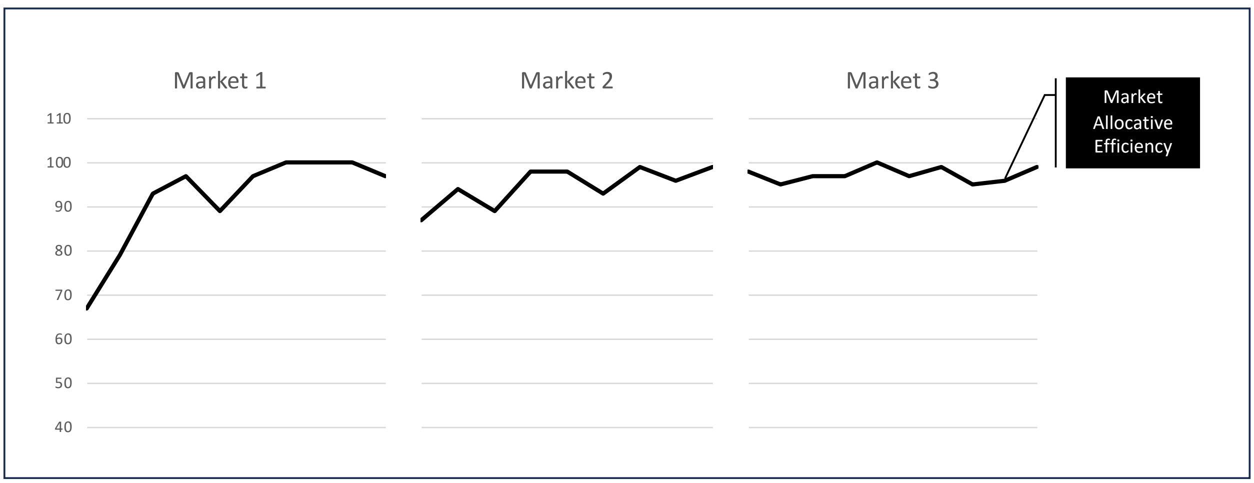

Figure 5.22: Allocative efficiency of market with ZIP_H agents following RS
[Source: Author's own]

The allocative efficiency in all three markets is very high when the agents learn about the market as the human traders learn in the DA market experiments. The market with box-shaped demand and supply schedules has the highest allocative efficiency followed by asymmetric and symmetric demand and supply schedules. The period-wise average allocative efficiency in each of these markets is 92 percent, 95 percent, and 97 percent in symmetric, asymmetric, and box-shaped market respectively. These results lead us to the conclusion that when the agents are allowed to learn then the inequalities in the market demand and supply are well addressed if compared with ZI agents without learning and ZIP agents with assumed learning behavior.

These results are also in line with the human experiments as they support the importance of intelligence and the learning of agents to be able to provide market efficiency. So, the market in the absence of intelligence is not able to provide a very high level of surplus to the agents as shown in the initial results of the DA market populated by ZI agents. Rationality is necessary for the market agents otherwise market by itself doesn't lead to the highest possible surplus.

In addition to allocative efficiency, the convergence of transaction prices is also an important measure to gauge efficiency. The next section deals with it.

5.2.4.2. Price Convergence in ZIP-populated Market with Randomized TS

To assess the market performance of ZIP_H agents in terms of price convergence in a randomized trading sequence all three types of market (symmetric, asymmetric, and box-shaped) are evaluated again. If the transaction prices converge toward the competitive equilibrium price level, then it means the actual outcome of the simulated market is getting closer to the theoretically predicted outcome. The transaction prices for these markets are illustrated below.

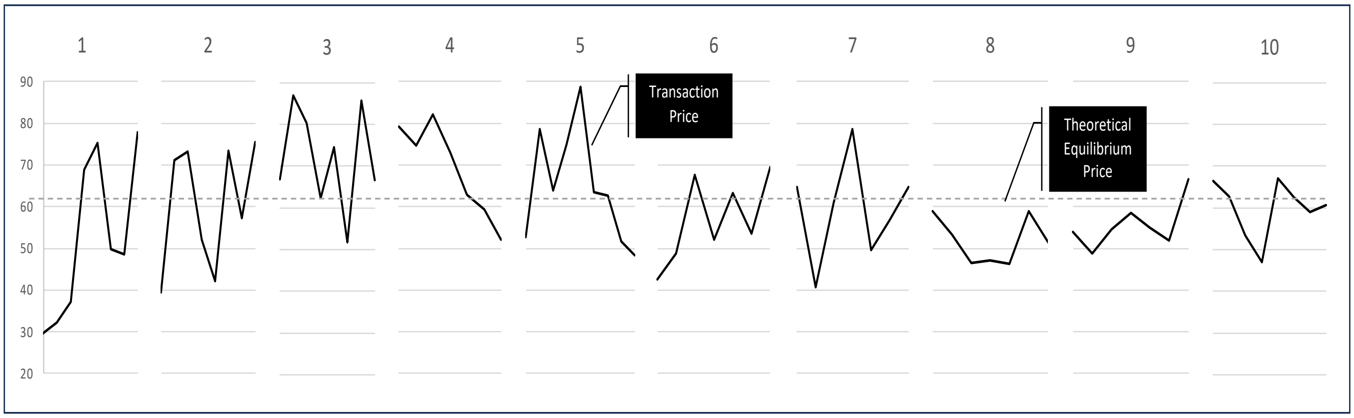

Figure 5.23: Period-wise TP of the market with a symmetric S&D schedule

[Source: Author's own]

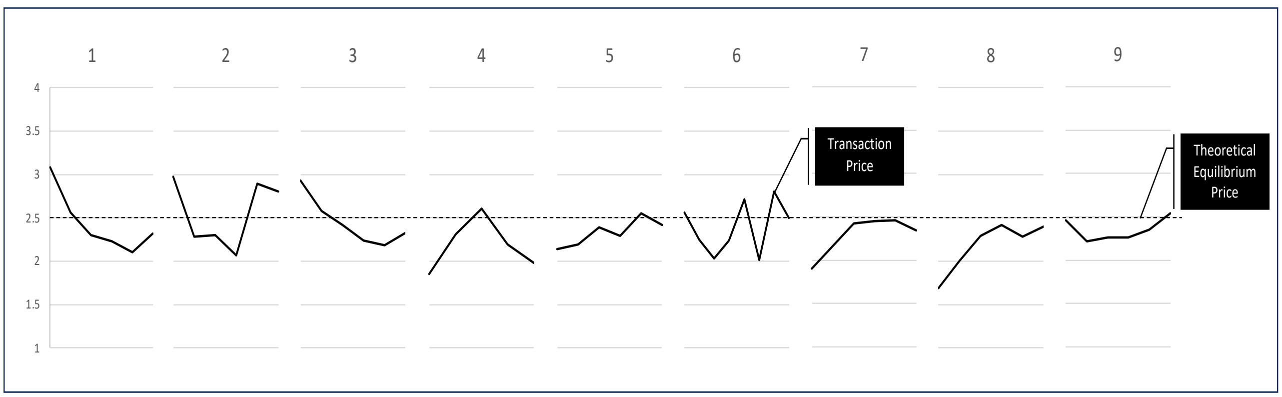

Figure 5.24: Period-wise TP of the market with asymmetric S&D schedule

[Source: Author's own]

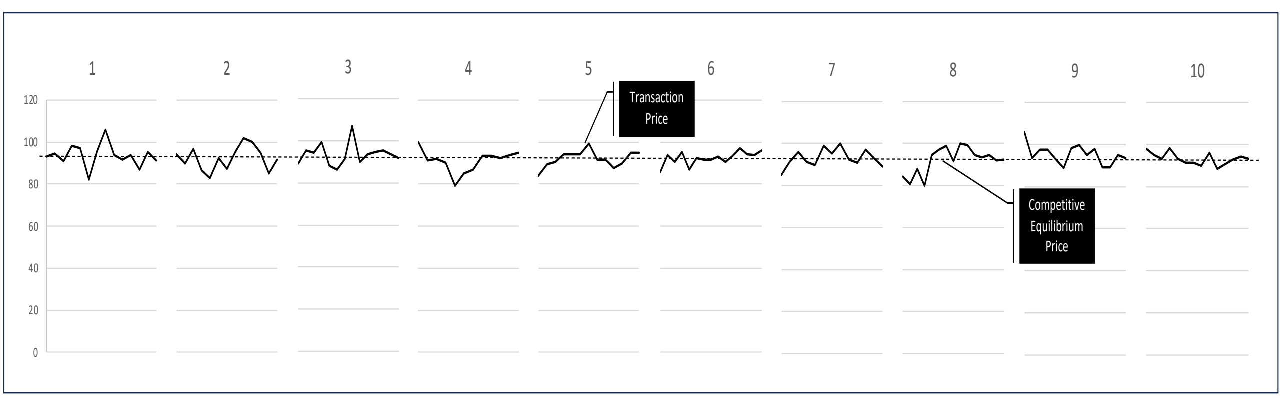

Figure 5.25: Period-wise TP of the market with box-shaped S&D schedule

[Source: Author's own]

The transaction prices for all three markets show strong convergence to competitive equilibrium price levels within each period and across the periods. In each period, over the trades, the transaction prices are getting close to the theoretical equilibrium price level, but this convergence is weak. The convergence of prices over the trading periods is considerably strong, especially in asymmetric and box-shaped markets.

These price convergence results align with the earlier output of allocative efficiency. In these simulated markets with randomized trading sequences populated with ZIPH agents, price convergence occurs. However, it is not as strong as in ZIPH-populated markets with Marshallian trading sequences.

The double auction market with the Marshallian trading sequence has been more efficient in terms of providing a higher surplus to agents as well as price convergence towards the competitive equilibrium level. These results of higher market efficiency, as predicted by competitive equilibrium theory, are not universal. The reason is when we change the trading sequence – while all the other market parameters like learning mechanism, and S&D schedules are constant – the market efficiency is compromised to some extent. However, this decline in market efficiency is not as broad as it is for ZI agents without any learning mechanism.

Till now, two types of market efficiency measures have been discussed. The next section deals with the last measure of market efficiency i.e., trade volume efficiency.

5.2.4.3.Trade Volume Efficiency of ZIP-populated Market with RS

Trade volume efficiency is another measure of market efficiency along with allocative efficiency and price convergence. Trade volume efficiency is also compared for the ZIP_H-populated market with varying demand and supply schedules.

Trade volume efficiency shows a high level of efficiency as in both markets (asymmetric and box-shaped) the efficiency is 100 percent except for one transaction. The trade volume efficiency is lower in symmetric demand and supply scheduled markets. This occurs because extra-marginal traders trade with intra-marginal traders. As a result, some potential intra-marginal agents are unable to participate in the trade. It leads to a decrease in the number of trades as a percentage of the competitive number of trades in each of these markets.

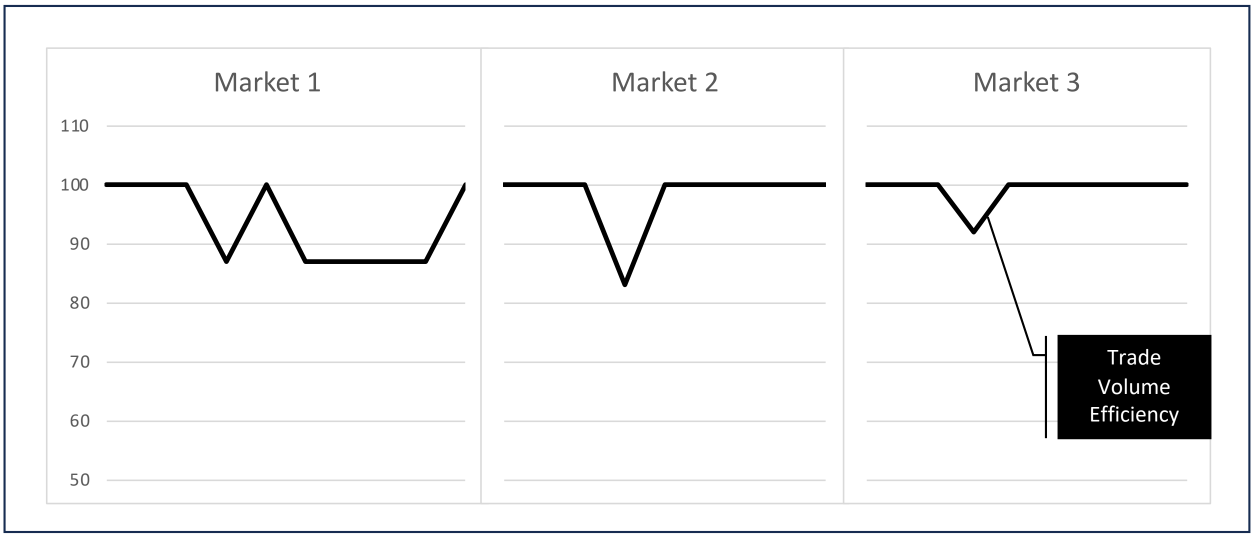

Figure 5.26: Volume efficiency of market with ZIP_H agents following randomized sequence [Source: Author's own]

When compared with the results of ZIP_H agents with Marshallian trading sequence, the difference is not huge as in that market trade volume efficiency was also higher as it is here. These results show that the trade volume is a measure of market efficiency that provides high-efficiency values irrespective of the trading sequence.

Whereas the market efficiency for the ZIP_H-populated market is visibly higher for the Marshallian trading sequence than it is for the Randomized trading sequence. These results explain the sensitivity of market outcomes and their efficiency to the microstructure. It means changing the details, regarding how the simulated market is set up, the market efficiency keeps altering. The efficiency of the market is sensitive to the trading sequence, type of S&D schedules, and the learning behavior of the agents involved in the market.

The results imply that even slight adjustments to the details of market setup can lead to significant alterations in market efficiency. Factors such as the choice of trading sequence, the structure of demand and supply schedules, and the learning behavior of market participants all exert considerable influence on market dynamics and efficiency.

In essence, these findings elucidate the intricate interplay between market microstructure and efficiency, emphasizing the need for careful consideration and optimization of market design. By understanding how different configurations impact market outcomes, policymakers and market participants can make informed decisions to enhance overall market efficiency and effectiveness.

CHAPTER 6

IMPLICATION OF RESULTS

Policy Implication in the Labor Market: Minimum Wage and Unemployment

6.1. Introduction

The widely used supply and demand (S&D) model in economic theory predicts a negative relationship between minimum wage and employment levels. It suggests that minimum wage acts as a form of price rigidity, leading to higher unemployment. This supports the argument against minimum wage laws and other price rigidities.

These predictions are contingent on assumptions inherent in the classical S&D model, assuming a competitive labor market with full information and no search or transaction costs. This may not fully align with real-world labor market conditions.

This research reevaluates S&D model predictions on minimum wage and employment. It utilizes an agent-based model (ABM) to scrutinize the theory. Initially, a baseline ABM model is established, adhering to competitive market theory assumptions with relaxed rationality assumptions. Preliminary findings suggest consistency with competitive market predictions.

Subsequently, the study introduces search and transaction costs to the baseline model, aiming to elucidate deviations from expected theory outcomes.

The initial outcomes of the S&D model are derived in the absence of market intervention and regulations. Competitive market theory contends that any form of intervention is detrimental to market efficiency, leading to a decline in overall market effectiveness. Various types of interventions, such as price stickiness, taxes, and quotas, are commonly introduced in markets. This study focuses on exploring a specific form of price stickiness, acknowledging the impossibility of addressing all types comprehensively. Price stickiness, particularly in the form of minimum wage fixation, is considered detrimental to the economy, impeding the free operation of supply and demand forces, and hindering the efficient allocation of resources.

According to the S&D model, a minimum wage set above the equilibrium level is predicted to result in a reduction in employment in the labor market. While these theoretical predictions are widely documented in economics textbooks, certain studies in the literature, exemplified by Card and Kruger (1993), present significantly different empirical findings. Their investigation in the restaurant market indicated that an increase in the minimum wage did not lead to higher unemployment but rather resulted in increased employment (Clemens and Wither, 2014). Limited literature has delved into the reasons behind these contradictory results, particularly concerning the role of search and transaction costs. This study aims to fill this gap by applying an agent-based model (ABM) to assess the relationship between an increase in the minimum wage and a decrease in employment levels in the context of search and transaction costs.

This study, as its third research focus, examines the impact of market intervention on market efficiency. Commonly, any form of market intervention is perceived to result in societal welfare loss, potentially decreasing overall efficiency. The choice of welfare measure is crucial, as altering it can influence model results and policy implications.

Traditionally, market efficiency is assessed by considering the total surplus earned by all market traders. In the labor market, welfare is often gauged by the total profit of firms and the surplus of laborers. However, this traditional measure neglects the number of unemployed individuals, emphasizing earnings over employment.

This study proposes a novel welfare measure – market transaction level – as a superior indicator of market efficiency. Two reasons support this choice:

1. The societal impact of unemployment outweighs the lower surplus in employed individuals. A market with a higher surplus but fewer employed individuals may result in a greater loss to society than a situation with more jobs and a lower surplus.

2. Positive gains can still be achieved with a surplus below efficiency levels, as long as employment increases. Both suppliers and demanders benefit even with a reduced surplus.

By shifting the market's focus from profit pursuit to achieving full employment, overall welfare may increase. In the labor market, efficiency may be better assessed by resource utilization rather than prioritizing higher profits with lower employment. Thus, this third section aims to evaluate market performance using a new welfare measure, contrasting with the existing measure of allocative efficiency, i.e., surplus.

6.1.1. Objectives

This chapter aims to emphasize the policy implications of the research, focusing on the labor market. The central theme involves testing the pervasive prediction of the S&D model, suggesting that minimum wage laws and market frictions lead to increased unemployment. The objectives of this chapter are:

1. Assessing the impact of frictional costs on employment levels in the labor market.

2. Explaining the relationship between minimum wage and unemployment with and without market frictions.
3. Investigating the welfare impact of minimum wage on labor market efficiency using alternative welfare measures.

6.1.2. Research Contribution

This research significantly advances our comprehension of the labor market, particularly in the realm of minimum wage policies and market efficiency. It begins by reassessing the predictions of the widely applied supply and demand (S&D) model, specifically the negative correlation it posits between minimum wage and employment. Employing an agent-based model (ABM), the study surpasses classical assumptions, providing a more nuanced exploration of the labor market dynamics.

Recognizing the inadequacies of classical assumptions, the research introduces search and transaction costs into the ABM model, creating a more realistic representation of the labor market. This research aims to bridge the gap between theoretical predictions and empirical findings, acknowledging the complexities introduced by interventions like price stickiness.

The study delves into the concept of price stickiness, focusing particularly on minimum wage fixation, shedding light on the intricate interventions that can affect the efficient allocation of resources in the market.

Building on empirical findings from studies such as Card and Kruger (1993), the research highlights instances where real-world outcomes contradict the theoretical predictions of the S&D

model. For example, in the restaurant market, an increase in minimum wage led to increased employment, challenging conventional wisdom.

Introducing a novel welfare measure – market transaction level – the research proposes an alternative to traditional measures like total surplus. This innovative approach prioritizes employment levels over earnings, recognizing the societal impact of unemployment and the potential for positive gains even with a surplus below efficiency levels.

Advocating for a shift in market focus from profit pursuit to achieving full employment, the research suggests that overall welfare may increase. This emphasis on resource utilization in the labor market, as opposed to prioritizing higher profits with lower employment, provides a fresh perspective on assessing market efficiency.

In summary, this research challenges traditional economic models, incorporates real-world complexities, and proposes alternative welfare measures. It enriches our understanding of the labor market, paving the way for more nuanced policy considerations and discussions surrounding minimum wage laws and market interventions.

6.1.3. Theoretical Framework

To develop the market environment of the ABM, we used the pre-defined model in the methodology section. This section is divided into two parts. Firstly, the trading sequence of Gode and Sunder (1993) is used to develop the baseline model of S&D. This baseline model doesn't have any government intervention nor does the search and transaction cost involved. The purpose here is to first set up the baseline model before introducing any complexities and see if the baseline S&D model gives us results in line with the competitive market theory predictions.

As the second step, market interventions are introduced in the model at two levels. First, market frictions are introduced in terms of government involvement in the labor market to provide at least a sustenance level of wages to laborers. For this purpose, minimum wage law is introduced in the market and its impact is checked at three different levels i.e., minimum wage lower than equilibrium level, at equilibrium, and higher than equilibrium level. The second kind of market friction is introduced in the two types of costs in the market faced by the agents i.e., search cost and transaction cost. These costs are introduced at high and low levels.

For the third objective, a new trading sequence is introduced in the microstructure of the market named matching trading. It is introduced to evaluate the welfare impact of the market if the welfare measure is changed from maximization of surplus to full employment in the labor market. Instead of following the Marshallian trading sequence, the matching principle is now used. Firms and laborers submit their bids and ask prices to the market representative. The market representative then matches the agents in a way that maximizes the employment level[39].

6.1.3.1. Baseline model: no Friction and no market intervention

The baseline model with no minimum wage imposition, no search cost, and no transaction cost has the following corollaries.

a. All the market agents have the reservation price i.e., the maximum affordable wage for the firms and the minimum acceptable wage for the buyers.
b. Firms are allowed to select the bid price randomly between the maximum affordable wage and a minimum selected value (i.e., 25 in this case) while the laborers are allowed to select

[39] There exists a tradeoff between these two welfare measures. When the market pursuit to maximize the surplus the employment level gets minimized and vice versa.

the asking price between their minimum acceptable wage and the maximum value (i.e., 135 here).

For the firm: $f_i = U\{25, maw_f\}$ *Equation 1*

For the laborer: $l_i = U\{maw_l, 135\}$ *Equation 2*

Where f_i is any firm from the sample of all the firms that may have the bid price (f_i) selected between 25 and the maximum affordable wage (maw_f) for each firm respectively from the continuous uniform distribution. Similarly, for the laborer, the ask price (l_i) is selected between the minimum acceptable wage (maw_l) for each laborer and 135 (i.e., a maximum wage that any laborer may ask) from the continuous uniform distribution. Once all the bid prices for the firms and the ask prices for the laborers is selected then we come up with the following lists of firms and laborers.

Firms with bid prices: $f_{i,\,bid} = U\{f_1, f_2, f_3, ---, f_n\}$ *Equation 1.1*

Laborers with ask prices: $l_{i,ask} = U\{l_1, l_2, l_3, ---, l_n\}$ *Equation 2.1*

Here $f_{i,\,bid}$ is the list of all the firms with selected bid prices and $l_{i,ask}$ is the list of all the laborers with their respective ask price, and 'n' is the number of firms and the number of traders[40].

c. When at least one firm and one laborer enter the market, they choose the trading partners with whom they can make the highest profit. So, the firm with the highest bid will trade with the laborer who has the lowest ask among all the available laborers. This is a well-known Marshallian trading sequence.

[40] Here the number of firms and the number of laborers is assumed to be equal. To make it simple here one laborer means the set of laborers with the same skills required by each firm.

The list 'T_r' represents the list of all the traders in the market including all the firms ($f_{i, bid}$) and all the laborers ($l_{i, ask}$). Let's have a subset of T_r i.e., T_r' that is the collection of traders chosen randomly from the list T_r to be entered in the market.

T_r' *is the subset of* T_r: $T_r' \subseteq T_r$ *Equation 4*

After selecting the subset of traders who enter the market (T_r'), it is to make sure that at least one firm ($f_{i, bid}$) and at least one laborer ($l_{i, ask}$) are in T_r'. For this purpose, there are the following conditions to meet.

For trade: $\exists f_{i, bid} \in T_r' \wedge \exists l_{i, ask} \in T_r'$ *Equation 5*

There exists at least one firm in ($\exists f_{i, bid} \in Tr$) and exist at least one laborer in ($\exists l_{i, ask} \in Tr$). Once the traders are ready to trade in the marketplace, the trading condition is checked. The trade happens only between the firm with the highest bid price and the laborer with the lowest ask price. It can be denoted as below.

$\forall \max (f_{i, bid}) \in T_r', \forall \min (l_{i, ask}) \in T_r' : f_{i, bid} \geq l_{i, ask}$ *Equation 6*

d. After deciding about the trading partners, the traders are then allowed to trade at the price that is the average of the bid price of the firm and the ask price of the laborer at which they are willing to provide services.

6.1.3.2. Impact of frictional costs on employment

After constructing the baseline model, the next step is to introduce the friction in the market. These frictions are of two types (search cost and transaction cost), and both are incorporated at two levels (low and high cost).

The search cost is defined in terms of the availability of information and access to the counterparty in the market. For instance, how many firms the laborer can look for or access to find a job? In case of high search cost the maximum access to the counterparty for both sides equals 1. Whereas, for the low search cost case, any agent has access to up to 4 agents from the counter side to explore the trade opportunity. It means any laborer can access randomly any four firms to look for a job at or above the bid price.

For the transaction cost, two particulars constitute it. One is the number of transactions that every agent can do in one period in the given market microstructure. It is limited to one as a laborer can work only in one firm at a time and similarly, the firm is entitled to hire only one batch of laborers from the market to meet the production needs. The other particular transaction cost is based on the selection of bid and ask prices for the agents. If the bid and ask prices are selected from a wider range, the transaction cost is considered high. This range is between the maximum affordable wage and any minimum level for the firms. For laborers, it is between the minimum acceptable wage and any highest level. For the low transaction cost Equations 1 and 2 are transformed by decreasing the range or the potential profit that the agents may earn. With the low profit the possibility of getting successful trade increases. As shown in equations I and II below, the firms are entitled to select the bid price at which they are willing to hire the laborer between 0 and 10 percent margin rather than the maximum affordable wage.

$$\textit{For the firm: } f_i = U\,\{(maw_f - 10\%\text{ of } maw_f),\ maw_f\} \qquad \textit{Equation I}$$

$$\textit{For the laborer: } l_i = U\,\{maw_l,\ (maw_l + 10\%\text{ of } maw_l)\} \qquad \textit{Equation II}$$

It allows the agents to have a lower transaction cost as the chances of their trade increase due to lower profitability.

6.1.3.3. Minimum wage imposition

After incorporating the market frictions in the model, the next step is to introduce government involvement in the market. In the labor market, minimum wage laws are introduced to examine their impact on the employment level in the labor market which aims to serve the second objective of this chapter. Minimum wage laws are introduced at three levels as follows.

a. Minimum wage below market equilibrium
b. Minimum wage at market equilibrium
c. Minimum wage above market equilibrium

The standard S&D model predicts that the minimum wage only above the equilibrium level increases the unemployment level but the minimum wage at or below the equilibrium level does not make any difference (Varian, 2014). The reason behind the non-effectiveness of minimum wage law, when it is at or below the equilibrium level, is because of the trading sequence. In the case of the Marshallian trading sequence, only the intra-marginal traders are allowed to trade with each other, and all the extra-marginal traders are kept inactive. The reason behind this is the purpose served by the Marshallian trading sequence which is to maximize the market surplus. The market surplus can only be maximized if the traders with extreme shot prices (laborers with lowest ask prices and firms with highest bid prices) at both sides of the market first trade with one another. As a result of this trading, there remains no incentive for the extra-marginal traders (who lie on the right side of the equilibrium) to get involved in trading. This is why economic theory predicts the significance of minimum wage laws only when it is above the equilibrium level.

6.1.3.4. Optimizing market prosperity: a strategy to elevate the overall welfare

The third objective here is to explore the possibility of increasing the market welfare of the participants. The existing measure of welfare (maximization of surplus) shall not be generalized to all markets, or it shall not be used for all purposes. Changing the welfare measure of the market efficiency market may lead to different results. When using the surplus as the measure of welfare the profit of successful traders increases but with an opportunity cost i.e., a low number of trades in the market. If the cost of not getting successful trades is considered, it becomes evident that this cost is way higher than the cost of losing the surplus as the tradeoff.

As per the S&D model, all the intra-marginal traders shall successfully get into trade and the sum of their surplus shall be maximized (which is achieved by following the Marshallian trading sequence). But having such a market mechanism keeps all the extra-marginal traders out of the market. If these extra-marginal traders don't trade, then the market experiences no loss[41]. So, if the market surplus is used as a measure of market efficiency, then the loss of all left-out traders is not considered.

In addition, in the labor market, the traders announce their bid and ask the price at which they want to trade after covering the cost and the redemption values. According to the competitive market theory, the amount of gain should be normal, and no trader should be able to earn an abnormal surplus. But if the Marshallian trading sequence is followed, as in the literature (Plott and Smith, 2008), then intra-marginal traders positioned at the extreme left of the equilibrium are allowed to have abnormal returns which go in contradiction with the theory prediction. The pursuit of achieving maximized surplus leads to abnormal returns for few traders in the market. As there is a tradeoff between the surplus and the number of traders (employment level) the welfare in terms of maximization of surplus causes unemployment in the market.

Another reason to switch away from the existing welfare measure is that the cost of not having a job is much higher than the cost of gaining less surplus. The laborer who is unsuccessful in getting

[41] The reason for not having any loss to the overall market is that all extra-marginal traders have their maximum affordable wage (for firms) below the equilibrium level. For laborers, their minimum acceptable wage is above the equilibrium level. When the expected surplus is calculated for these traders, it equals zero or is negative.

employed faces huge costs as the whole family suffers from this loss. It is why the cost of gaining less surplus can never be closer to the cost of having no job and sleeping hungry along with family. This stance motivates the use of employment level as the measure of welfare instead of counting on the amount of surplus gained.

A holistic overview of the theoretical framework is provided in the box below.

Table 6.1: Overview of the theoretical framework of labor market interventions

Model/Intervention	Market Friction	Market Intervention
Baseline Model	No	No
Market with frictions	Search and transaction costs	No
Minimum wage imposition	No	Below, at & above equilibrium
Minimum wage imposition	Search and transaction costs	Below, at & above equilibrium
Market welfare	Search and transaction costs	No
Market welfare	Search and transaction cost	Below, at & above equilibrium

[Source: Author's own]

As described earlier, the S&D model is tested in various contexts while starting by establishing the baseline model without any market friction (search and transaction cost) and market intervention (minimum wage laws). After that friction is introduced in the market and its impact is evaluated on the employment level. In the third model, market frictions along with minimum wage laws are introduced. Lastly, the market welfare impact is measured through measures other than surplus maximization in the presence of only market frictions and in the presence of market interventions as well.

The next section explains the data, afterwards the results of all the models discussed above are presented in the empirical result section, and the last section is dedicated to the conclusion and policy implications.

6.1.3. Data

A baseline ABM model is set based on the labor demand and supply in Pakistan. The data for the distribution of wage rates is taken from the Household Integrated Economic Survey (HIES) available in quintiles (Government of Pakistan, 2019). The demand and supply elasticities of the labor market in Pakistan are taken from the literature. The labor supply elasticity is found to be relatively inelastic as the supply is less responsive to changes in the wage rate and for the developing countries, its value is 0.4 (Brooks *et al.,* 2019)[42]. The data for the labor demand elasticity is taken from Yasmin and Khan (2011) i.e., -0.87 who calculated the elasticity based on Pakistan's Census of Manufacturing Industries[43].

The labor S&D graphs drawn in the figure below are approximated by the wage distribution in Pakistan along with labor demand and supply elasticities. The labor demand is relatively elastic as compared to the labor supply curve. The equilibrium wage level is approximated at the wage rate of 75. There are three levels of minimum wage introduced in the model i.e., below, at, and above the equilibrium wage level (P^1, P^e, and P^2) respectively.

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[42] The data for the labor supply elasticity is not readily available for Pakistan, and it is the reason the data for the middle-income countries is approximated while assuming that the skill set and the population (as the leading measure of labor supply elasticity) don't change rapidly due to change in wage. In addition, due to less labor movement across the border for developing countries like Pakistan, the labor supply for unskilled and semi-skilled workers remains unchanged.

[43] The elasticity of demand is taken from Yasmin and Khan (2011) and the elasticity of supply is taken from Brooks *et al.,* (2019). The values of these elasticities are presented in the table below along with some other estimates from the literature. The rational of selecting the values of labor supply and demand is based on the recent estimates available. See appendix 3.

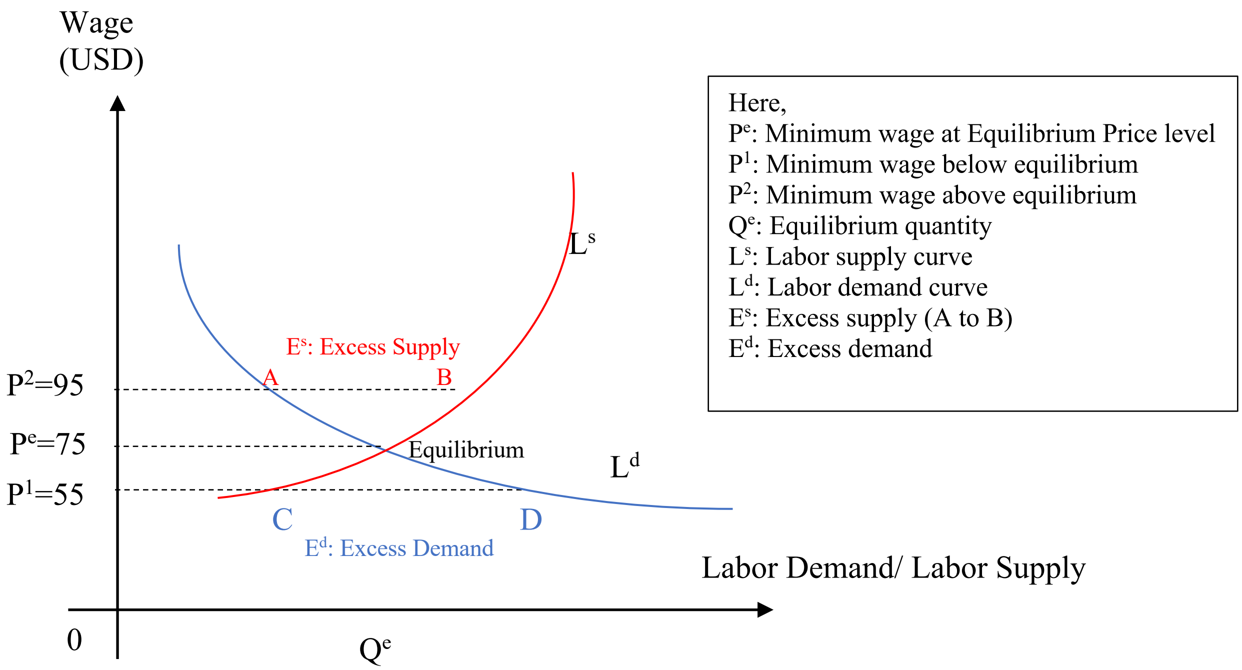

Figure 6.1: Labor demand and supply with minimum wage levels

[Source: Author's own]

The level of minimum wage is applied at three levels i.e., below, at, and above market equilibrium level. These levels of minimum wage are suggested by the expert in the interviewees[44]. The minimum wage level below equilibrium is 55, at equilibrium is 75, and above equilibrium is 95 USD.

The next section provides the results of simulations for all the models i.e., with and without government interventions, and with varying search and transaction costs.

[44] Three interviews were conducted for this purpose. Two of these interviews are conducted by the Ministry of Finance and one is conducted by the Security and Exchange Commission of Pakistan. As per the expert advice, the equilibrium wage level is suggested at 75 USD per month for the unskilled worker which is lower than the minimum wage imposed by the government. They suggested a lower-than-implied level because of the lack of application of minimum wage laws across the country. Similarly, in the informal sector, the minimum wage laws are hardly applied or applied at a lower than announced wage. So, it is suggested to test the results for three levels i.e., below, at, and above the equilibrium level of minimum wage.

6.2. Simulation Results

As explained in the theoretical framework of this chapter, the simulations are divided into various sections based on the presence of market friction and the implementation of government law in the market. These results are segregated into four sections. The first section provides the results of the baseline model with no market friction and intervention but just led the foundation to later introduce different market scenarios.

After providing the baseline of the agent-based model, the second step is to bring in market friction in the model and see how it impacts market efficiency. These market frictions of two types i.e., search cost (low and high) and transaction cost (low and high). The aim here is to explore the impact of these market frictions on the labor market in terms of its efficiency.

In the third stage, the minimum wage law is introduced at three levels (below, at, and above equilibrium wage) along with the search and transaction cost in the market. The purpose here is to examine if the minimum wage law leads to an increase in unemployment as rationalized by the competitive market theory. First, these laws are introduced only with the imposition of minimum wage laws. Then minimum wage laws are implemented at three levels along with the market frictions (search and transaction costs).

The last section of these results is dedicated to the comparison of different welfare measures. Earlier results apprise the model efficiency of the S&D model based on the surplus level during the trades. Whereas, this section aims to introduce a new measure of market efficiency i.e., trade volume efficiency as it focuses on maximizing the number of trades or the employment level instead of surplus maximization.

The results of all these four sections are illustrated now.

6.2.1. Simulation results of a baseline model

The results of the first simulations come from the S&D model when there is no market friction and presence of no government involvement. The results are presented in two ways. One is in terms of the behavior of transaction prices over the periods and the other is the average of transaction prices over these periods[45].

Figure 6.2: Labor S&D with no friction and no government intervention

[Source: Author's own]

The results of the baseline model show market information for three variables. First, the bid price at which firms are willing to hire laborers. Second, the ask price at which laborers request to be employed and provide services. Third, the transaction price at which both firms and laborers agree to finalize the employment contract. Lastly, the equilibrium price, which is the competitive market equilibrium level. Here to examine the impact of policy intervention in labor, the S&D schedule as well as the equilibrium level of wages is kept constant to observe the market behavior across the periods.

[45] All the simulation results are iterated for 50 periods to calculate the average behavior of the market and the robustness of the model. However, the results presented in the graphical analysis are presented for the 10 periods only.

The boxes at the top of the figure show the period number (from 1 to 10) and the boxes at the bottom of the figure show the number of trades or the employment level in each period. The horizontal axis of the figure is the number of trades while the vertical axis represents the level of wages in the labor market. The equilibrium wage is 75 USD per month for period 1 and in this period the total number of successful contracts is 10. These results are based on the Marshallian trading sequence as first used by Gode and Sunder (1993) for the ZI agents. Although the transaction prices seem to have random patterns, the wages converge to the competitive equilibrium level over the trades. The fluctuation of the contract price (transaction price) declines over the trade exhibiting the convergence process[46].

The results of market efficiency along with period-wise average transaction price and total surplus are provided in the table above. The average contract wage over the period increases first and then it converges back to the equilibrium wage level. The level of market surplus gained from trade is mirrored in the market efficiency. The market efficiency shows the total surplus gained by all the firms and the laborers in one period as the percentage of competitive market level surplus i.e., 500 in this case. The market efficiency is higher but then it decreases to 87 percent in the last period. An increase in market efficiency is caused by the wider difference between the contract wage and the equilibrium level of wage. Theoretically, the market efficiency shall be higher in the early contracts and start decreasing over the trades. The reason for declining market efficiency within one period is that extra-marginal traders with the highest maximum affordable wage and minimum

[46] As discussed earlier, the convergence of contract prices towards equilibrium wage is achieved depending on what trading sequence is being followed. In the case of the Marshallian sequence, a significant amount of convergence is witnessed but it may not happen in other trading sequences i.e., randomized trading sequence.

acceptable wage are more likely to trade first. These traders are expected to have a higher surplus. However, the surplus starts decreasing with each trade (as shown in Figure 6.2).

Table 6.2: Period-wise market efficiency of the baseline model

Period	Average C. W[47]	Total Surplus	Surplus Efficiency (%)
1	79**	475	95***
2	70***	465	93**
3	78**	445	89*
4	81***	495	99***
5	68***	490	98***
6	75	495	99***
7	70***	455	91**
8	75	488	98**
9	80***	480	96**
10	78**	435	87

Here, the level of significance is shown by *, **, and *** at 90%, 95%, and 99%, respectively.

[Source: Author's own]

These results support the prediction of competitive market theory as the S&D model leads to very high market efficiency in the labor market i.e., 95 percent on average. The trade volume efficiency, as per the competitive market theory, is also 100 percent[48]. So, the baseline S&D model provides robust results. This is evident as the simulations are repeated over 50 periods. The model supports competitive market predictions. It shows that the S&D model, in the absence of friction and market involvement, leads to efficiency results.

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[47] Here C.W denotes the wage decided between the firm and the laborer in each successful transaction.

[48] Trade volume efficiency is measured as the average number of trades in the period as the percentage of theoretically predicted trades in the competitive market i.e. 10 contracts in this case.

Now based on these results of the baseline S&D model, the next sections present the results when market frictions are introduced in the model.

6.2.2. Simulation results of S&D model with market frictions

After setting up the baseline model and checking the robustness of the S&D model, two types of market friction are to be introduced. One of these market interventions is the search cost and the other is the transaction cost. It is helpful to elaborate on these two costs before presenting the results. The search cost is the cost of the search for the job to earn or for the laborer to produce. The search cost limits the firms and the laborers to have access to all the employers and employees in the labor market at one point in time. The search cost is applied in two variations: low and high search cost. Laborers and firms are allowed to access at least 5 neighboring counterparties to secure a successful contract in the market. If a trader is unsuccessful in making a trade with their 5 recent neighbors, their need remains unmet for that specific period.

In terms of high search costs, all the traders are limited to having access to two adjacent counterparties. If the bid wage of the firm is less than or equal to the asked wage of the laborer, then the contract is finalized between them. Otherwise, both parties may go to maximum one the other counterparty.

The second type of friction introduced in the market is the transaction cost. It again carries two variations. The high transaction cost is when the agents have a high range of possible profit margins. In the prevailing literature, the ZI agents usually the agents are allowed to choose to bid (ask) prices, at which they want to contract, between their maximum affordable (acceptable) price and a selected minimum (maximum) value. The wider the given range from where the agent can select their shout prices, the greater the transaction prices. For the lower transaction price, the agents are allowed to have a shout price randomly between the redemption value (cost) with the 10 percent profit margin.

The result of this section is divided into four sections to explore the impact of market frictions on labor market efficiency and convergence as below.

a. Low search cost, low transaction cost.
b. High search cost, low transaction cost.
c. Low search cost, high transaction cost.
d. High search cost, high transaction cost.

6.2.2.1. Labor market with low search and low transaction costs

This section aims to provide evidence on the impact of search and transaction costs on the labor market in terms of efficiency i.e., the value of surplus from the contracts. The competitive market theory rationalizes that the in absence of any market friction the markets are more efficient than the markets with frictions. The S&D model, which is based on competitive market assumptions, shall provide the results in line with the prediction of competitive market theory. It means in the presence of market friction the surplus may decline as compared to the results in the previous section.

However, the results of the S&D model in the labor market show that over the periods the bid-ask spread decreases which leads to a decreasing surplus. The contract wage converges towards the theoretically predicted wage of the S&D model. These results are in line with the competitive theory predictions as well.

Figure 6.3: Labor market S&D with low search and low transaction costs

[Source: Author's own]

The average number of contracts in these periods was just equal to the number of contracts in the presence of no market frictions. The reason for not having a difference in the average number of contracts is the low market friction. It is expected that as this friction increases, the volume of successful contracts in the market will start declining.

Table 6.3: Period-wise market efficiency (with low search and low transaction costs)

Period	Average C. W	Total Surplus	Surplus Efficiency (%)
1	75	322	64***
2	82***	315	63***
3	75	440	88***
4	77**	330	66***
5	75	340	68***
6	73**	360	72***
7	72***	325	65***
8	75	360	72***
9	71***	300	60***
10	75	325	65***

Here level of significance is shown by *, **, and *** at 90%, 95%, and 99% respectively [Source: Author's own]

The decline in the market surplus over the period confirms the predictions of competitive market theory about the convergence towards equilibrium. So, in the presence of low transaction and low search costs, the results of the S&D model in the labor market do not diverge significantly from the S&D model with no market frictions.

6.2.2.2. Labor market with low search and high transaction costs

After exploring the labor market with the lowest search and transaction costs, now the transaction cost is increased by increasing the possible profitability range of all the agents. The expected results are that due to the increased profitability range the shout prices the surplus from contract may increase. But, as discussed before, there exists a tradeoff between the surplus efficiency and the trade efficiency which ultimately causes the market to have a smaller number of contracts in each period.

The results of S&D model populated with ZI agents is presented in the figure below. The bid-ask spread is relatively higher if compared with the labor S&D when there is low search and low transaction costs. But the spread between bid and ask decreases over the periods. It is the reason that the transaction prices, especially the last contract at the end of each period, is closer to the equilibrium level of contract price.

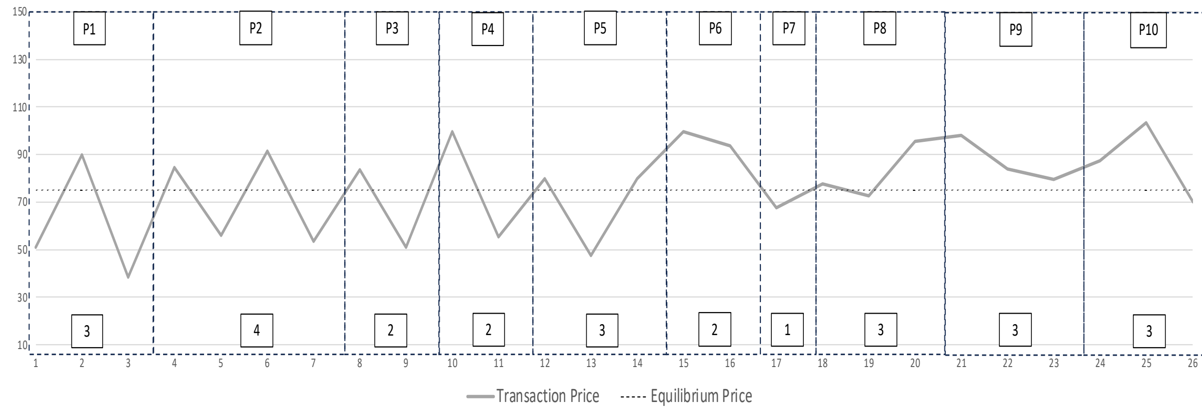


Figure 6.4: Labor market S&D with low search and high transaction costs

[Source: Author's own]

The total number of successful contracts in the labor market is 26 as compared to theoretical level contracts i.e., 500 contracts. However, with an increase in transaction prices, the average number of successful contracts decreases to only 2.6 per period.

Table 6.4: Period-wise market efficiency (with low search and high transaction costs)

Period	Average C. W	Total Surplus	Surplus Efficiency (%)
1	60***	70	14***
2	71	134	27***
3	67**	49	10***
4	78	96	19***
5	69**	71	14***
6	97***	60	12***
7	68**	28	6***
8	82**	170	34***
9	87***	147	29***
10	87***	123	25***

Here the level of significance is shown by *, **, and *** at 90%, 95%, and 99% respectively.

[Source: Author's own]

Similarly, an increase in the transaction cost also declines the average market efficiency from 68 percent (with low transaction cost) to only 19 percent (with high transaction cost). These results support the theoretical predictions of the S&D model that due to high transaction costs the market surplus efficiency may decline significantly. For the markets to be efficient these costs should be negligible otherwise it may cause friction in the labor market.

6.2.2.3. Labor market with low search and high transaction costs

The next variant of market friction is introduced with high search costs and low transaction costs. The search cost is increased when the laborers and the firms have a limit to have access to most 2 of their neighbor's positions. It means the laborers can search for the job at the nearest 2 firms, and the firm can search for a maximum of 2 laborers for a specific kind of job. With an increase in search cost the accessibility of the market agents to access the counterparty gets limited. This limitation creates friction in the market that leads to inefficient market outcomes.

It is expected that with an increase in the search cost the surplus as well as contract volume shall decline in the market. When the traders are not able to access all the other traders but have to choose from specific traders, then the possibility of maximizing the surplus gets compromised. This limitation of accessibility hurts the laborers as it causes an increase in unemployment. The results of simulations for the 10 periods are presented below.

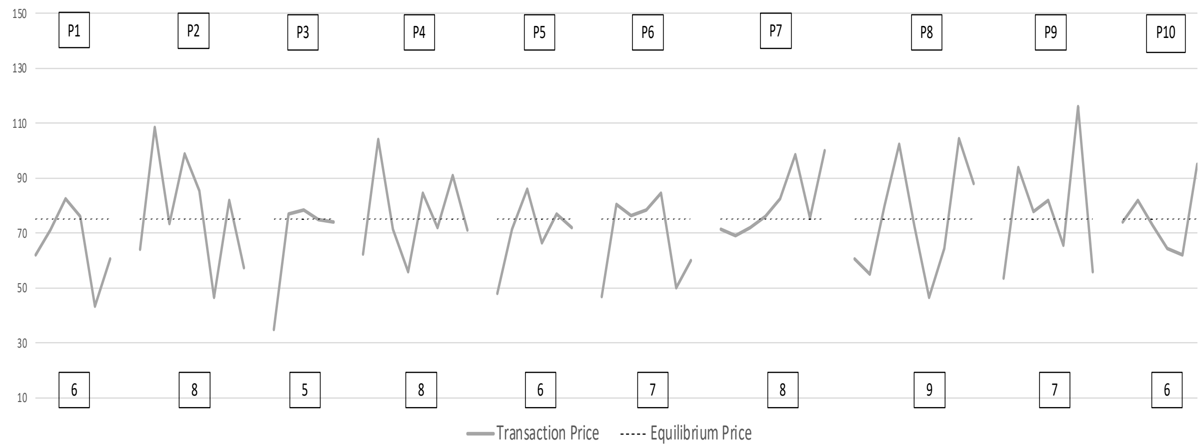


Figure 6.5: Labor market S&D with high search and low transaction costs

[Source: Author's own]

It is witnessed that the average number of trades in these 10 periods is lower than the S&D model with no market frictions. The baseline S&D model without frictions has an average number of successful contracts of 10 which is equal to the number of successful contracts with low search and transaction costs. However, when either the transaction or the search costs are increased to a high level then it leads to a decline in the average number of contracts per period.

Across all the periods, the market efficiency is significantly lower than the theoretically predicted level of efficiency due to an increase in the transaction cost. The average market efficiency decreases to only 58 percent with high search and low transaction costs from 94 percent for the S&D model with no market friction. In addition, the average number of successful contracts also declines to 7 only when compared with the baseline model, which has an average of 10 contracts per period.

Table 6.5: Period-wise market efficiency (with high search and low transaction costs)

Period	Average C. W	Total Surplus	Surplus Efficiency (%)
1	66***	260	52***
2	77	280	56***
3	68***	215	43***
4	77	340	68***
5	70***	330	66***
6	68***	280	56***
7	81***	325	65***
8	75	330	66***
9	78*	260	52***
10	75	275	55***

Here the level of significance is shown by *, **, and *** at 90%, 95%, and 99%, respectively.

[Source: Author's own]

These results show that market frictions cause inefficiencies, but these inefficiencies are more severe in case of high search costs than high transaction costs. So, the government shall focus more on subsiding the search cost for the market to be efficient.

6.2.2.4. Labor market with high search and high transaction costs

The last results of this section are related to the situation when both the search and transaction costs, are very high in the economy. The higher tendencies of these costs are one of the major reasons that amplify the unemployment level. For this reason, it is promising to explore the impact of high search and high transaction costs on market efficiency, wage levels, and the number of successful contracts.

Table 6.6: Period-wise market efficiency (with high search and high transaction costs)

Period	Average C. W	Total Surplus	Surplus Efficiency (%)
1	83**	62	12***
2	96***	63	13***
3	67**	113	23***
4	100***	65	13***
5	76	169	34***
6	83**	102	20***
7	67**	41	8***
8	74	45	9***
9	88***	45	9***
10	99***	60	12***

Here the level of significance is shown by *, **, and *** at 90%, 95%, and 99%, respectively.

[Source: Author's own]

When the market friction increases to a higher level it has a negative effect on market efficiency, on the contract wage, and number of successful contracts as well. Higher market frictions, including high search and transaction costs, lead to a decrease in the average market surplus to 77. The average market wage diverges from the competitive equilibrium level of 83.3. This causes the average number of contracts to decline to only 1.8 per period.

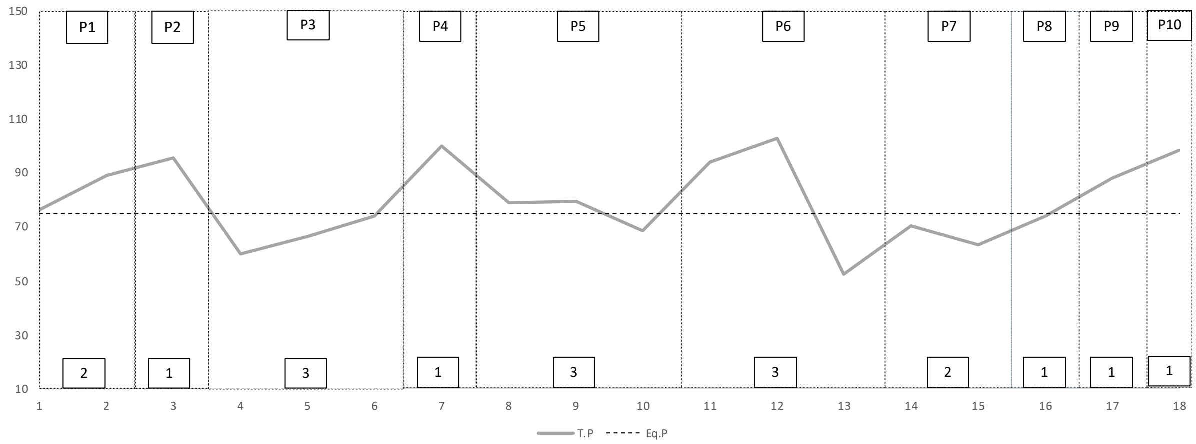


Figure 6.6: Labor market S&D with high search and high transaction costs

[Source: Author's own]

Divergence of wages away from the theoretical equilibrium level of wage causes the firms (buyers of the labor services) to face higher search and transaction costs as their surplus reduces more than the reduction in the surplus of laborers. The cost for firms is shown by a decline in efficiency as the surplus drops. For laborers, the cost due to market frictions is highlighted by a reduced number of contracts and increased joblessness. The average number of successful contracts in the market, with high search and transaction costs, is only 1.8 contracts per period.

The combination of market frictions has a deeper negative impact than the market with a higher level of one of these frictions. These results again call for government intervention to reduce the market friction in the labor market by decreasing the search and transaction costs. More integration in labor, efficiency in labor search, and lower transaction costs are the areas to work on to increase market efficiency.

6.2.2.5. Labor market with market frictions: Summarized comparison

This section attempts to summarize the impact of all the variations in market frictions on labor market efficiency. A comparison is made for all four variations across the wage convergence towards the theoretical equilibrium wage, number of contracts, and average market surplus. These results are summarized in the table below.

These results show that the market efficiency (in terms of surplus) is highest when no friction is present in the market but as soon as friction (as search or transaction cost) appears in the market, the predicted efficiency of the S&D model is compromised. It can be observed in the table above that as the wage level moves away from the theoretically predicted level, the average number of contracts declines to only 1.8 per period. Additionally, the market surplus declines from 94 percent to only 15 percent in the case of high search and transaction costs.

Table 6.7: Summarized period-wise impact of market frictions[49]

Variations in S&D Model	**Avg. Wage**	**Avg. No. of Contract**	**Market Surplus (Efficiency %)**
Baseline model: No market friction	75	10	472 (94%)
Model with **low** search and **low** transaction costs	77	10	342 (68%)
Model with **low** search and **high** transaction costs	75	2.6	95 (19%)
Model with **high** search and **low** transaction costs	74	7	290 (58%)
Model with **high** search and **high** transaction costs	83	1.8	77 (15%)

Here the level of significance is shown by *, **, and *** at 90%, 95%, and 99%, respectively.

[Source: Author's own]

[49] Here average wage is presented in USD.

All these results are in line with theoretical predictions of the S&D model as depicted by competitive market theory. In this model, till now, government intervention is recommended to decrease the market friction so that efficiency can be increased.

As the next step, this research tries to explore the impact of government intervention on the market. The government interventions are of various types. These include improvements in labor market information accessibility, skills development, and reducing hiring barriers. Other interventions involve labor market reforms to increase flexibility, subsidies to hire, and unemployment benefit reforms. Most importantly, there are minimum wage reforms.

The S&D model predicts that, as of market frictions, any kind of government involvement leads to market inefficiency and results in a declined market surplus and lower employment level. However, some of the studies in the literature show the results opposite to this prediction. For instance, in the case of government involvement by implying the minimum wage laws, the employment level increases instead of a decline (Card and Kruger, 1994; Dube, Lester, and Reich, 2010; Cengiz, Dube, Linder, and Zipperer (2019); and Reich, Allegretto, and Godoey (2017).

The next section is an attempt to measure the impact of market intervention in terms of minimum wage implications in the labor market.

6.2.3. Minimum Wage Implication in the Labor Market

The competitive market theory predicts that the obvious implication of minimum wage laws on the employment level is negative as it leads to higher market inefficiencies. These inefficiencies cause an increase in unemployment as caused by market frictions. As per the theory, the implication of wage law is not good for the market as it decreases the surplus as well as the employment level.

Whereas the empirical research in the real labor market states the impact of minimum wage laws on the employment level is opposite from the theoretical predictions. For instance, the famous study of Card and Kruger (1994) and Dube Lester and Reich (2010) shows the positive impact of the increase in the minimum wage on the level of employment.

This divergence of empirical results from the theoretical predictions of the S&D model motivates to explore the impact of minimum wage laws on unemployment. This purpose is served through 4 different models based on the presence of market frictions (along with its 4 variations) and without market frictions for 3 minimum wage levels i.e., low, at, and above the equilibrium level of wage (in total 12 models). A summarized description of these models is presented in the table below.

Table 6.8: Summarized description of models to evaluate the impact of minimum wage

Market Intervention	**Market Frictions**
Minimum wage:	Low search & low transaction cost
♦ Below equilibrium	Low search & high transaction cost
♦ At equilibrium	High search & low transaction cost
♦ Above equilibrium	High search & high transaction cost

[Source: Author's own]

The relationship between minimum wage increases and unemployment is complex. Proponents of minimum wage hikes argue that, under certain conditions, raising the minimum wage can potentially decrease unemployment. They believe this is because it addresses specific issues related to search and transaction costs. For instance, the firm may find it beneficial to pay higher wages to increase the productivity of workers, especially when there is a high search cost associated with finding the workers again. Similarly, when the wages are high the workers are more committed to their work, reducing the search and transaction costs for the firm.

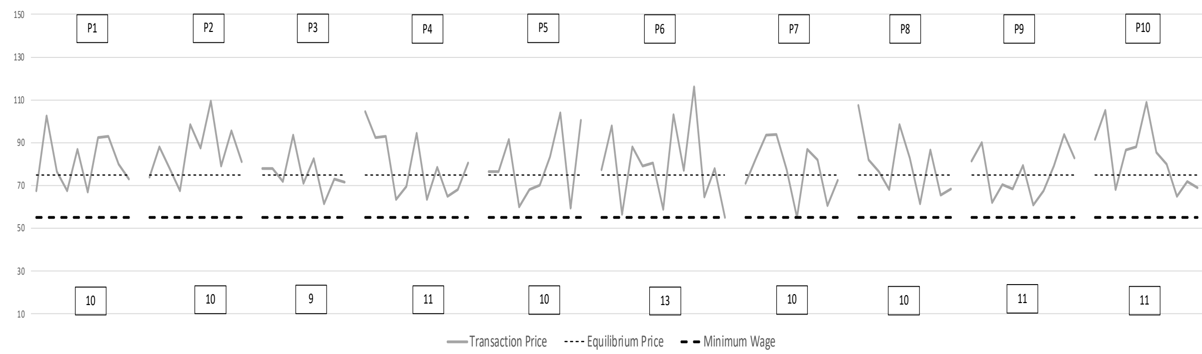
Based on the discrepancies between the empirical results and the competitive theory predictions, the presence of a complex relationship between the minimum wage and unemployment is required to be explored. Here the focus is on the number of successful trades as it shows the employment level in the labor market. The results of simulations of the S&D model with ZI-populated agents are provided in the next section[50].

Before introducing the market frictions, the first result is about the implication of minimum wage on the employment level without search and transaction cost and is considered as a baseline model.

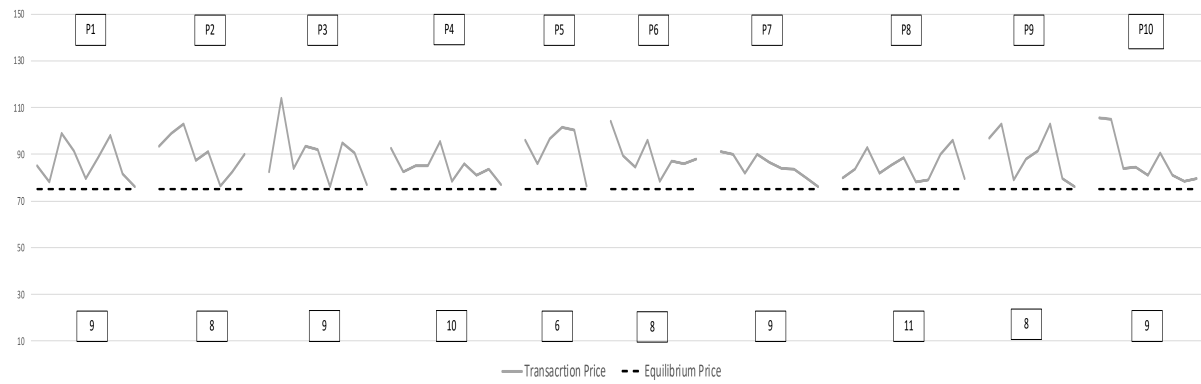
6.2.3.1. Imposition of the minimum wage: Baseline model

The results of the baseline model without market frictions demonstrate the impact of minimum wage on market efficiency. This model introduces the minimum wage at three levels i.e., minimum wage below, at, and above the equilibrium wage. The results of bid-ask shouts and the transaction price is presented in the figure below.

[50] Here the results for two variations (high search & high transaction costs, and low search & high transaction costs) of market frictions are provided based on the explanation of the positive relationship between the minimum wage and the employment level.



Panel A: Below equilibrium minimum wage



Panel B: At equilibrium minimum wage

Panel C: Above equilibrium minimum wage

Figure 6.7: Impact of minimum wage imposition on unemployment [Source: Author's own]

These results show that the unemployment level also increases with an increase in the minimum wage (in the absence of market friction). Without any minimum wage imposition, the average number of contracts in the S&D model is just equal to the theoretically predicted employment level i.e., 10. Furthermore, the competitive theory predicts that if the minimum wage is below equilibrium, it doesn't significantly impact unemployment. The same is the case here, as shown in panel A of Figure 6.7. When the minimum wage is applied in the labor market and is less than the equilibrium wage, the number of successful contracts is 10. This number is just equal to the theoretically predicted level of employment.

When the minimum wage is increased to a level equal to the theoretical equilibrium level, then it has a slight negative impact on the employment level as the average number of successful contracts decreases from 10 to 9 contracts per period. But as soon as the minimum wage level increases above the equilibrium wage level employment declines only to an average of 6 contracts per period as compared to a theoretical employment level of 10 in each period. The S&D shows that due to the imposition of minimum wage above equilibrium, the average employment decreases by 40 percent.

It is in line with the prediction of the S&D model that any market intervention, especially in the form of minimum wage imposition, leads to higher unemployment. After checking the robustness of the baseline model to ensure it follows the theoretically predicted results, the impact of minimum wage laws on market performance is explored. This exploration occurs in the presence of market frictions.

6.2.3.2. Application of minimum wage with market frictions

In the previous section, the minimum wage laws were introduced at different levels in the labor market without market friction. This baseline model is helpful in illustrating the S&D model results as proposed by competitive market theory. Now in this section, the aim is to try to explain the empirical results in the labor market that show a positive relationship between the increase in minimum wage and the level of employment.

This purpose is achieved by having four variations in search and transaction costs (low and high costs) across three levels of minimum wage in the market. Out of these four variations of market friction, two are notable. The first is low search and high transaction costs. The second is high search and high transaction costs. These two variations successfully explain the empirical results. They show how employment may increase with an increase in the minimum wage[51].

With an increase in the minimum wage, the bid-ask spread starts declining. This is because of the lower profit margin available to both the laborers and the firms. The number of successful trades or the employment level is way lower than the equilibrium level of employment. Competitive equilibrium theory suggests that the S&D model should achieve an average employment level of 10 trades per period. This equates to a total of 100 trades over 10 periods. However, due to search and transaction costs, the average employment level declines. It falls to only 1.3, 1.5, and 1.7 trades per period with a minimum wage below, at, and above equilibrium, respectively.

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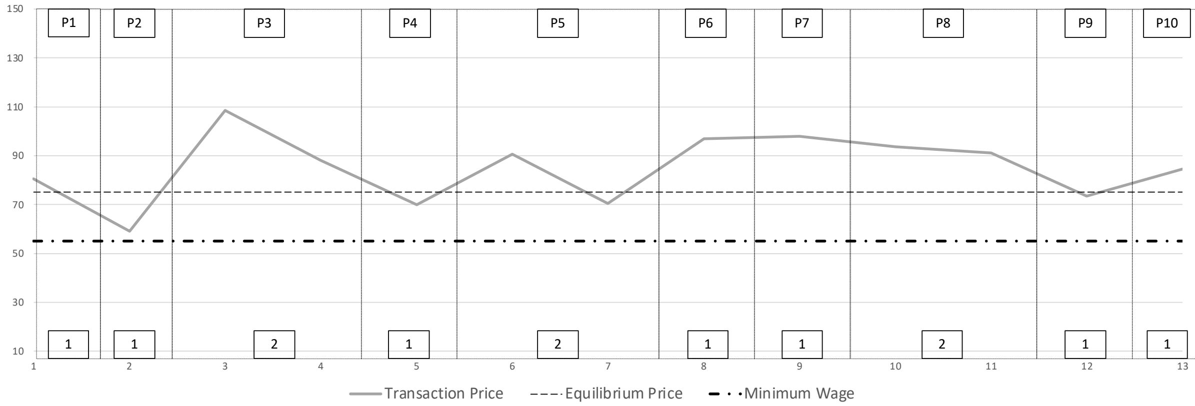
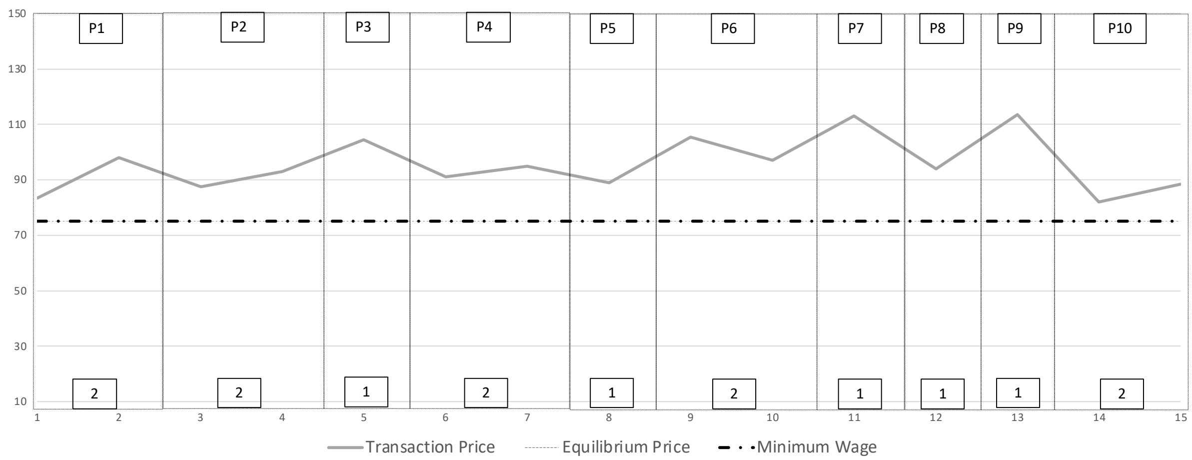
[51] The results of those cases are presented here where the S&D model successfully explains the phenomenon of position relation between the minimum wage and the employment level.



Panel A: Minimum wage below equilibrium



Panel B: Minimum wage at equilibrium

Panel C: Minimum wage above equilibrium

Figure 6.8: Impact of minimum wage law on unemployment with high search and high transaction costs [Source: Author's own]

Due to the decline in the employment rate, the market efficiency (in terms of total market surplus) also drops. It is shown in the table below.

Table 6.9: Impact of minimum wage on employment (with high search & high transaction costs)[52]

Min Wage	**Below Equilibrium**		**At Equilibrium**		**Above Equilibrium**	
Period	Avg. C.W	Efficiency	Avg. C.W	Efficiency	Avg. C.W	Efficiency
1	81*	14	91	11	105	11
2	59***	2	90	19	116	6
3	98***	13	105	10	114	10
4	70	14	93	14	109	10
5	81*	24	89	8	111	10
6	97***	10	101	18	116	5
7	98***	12	113	5	104	8
8	92***	16	94	9	117	6
9	74	10	114	10	113	8
10	85**	3	85	14	118	10

[Source: Author's own]

With no market frictions, the average per period contract wage (c.w) is 83 USD which remains the same for the minimum wage below equilibrium but then increases to 97 and 112 USD when the minimum wage is at and above equilibrium, respectively. In terms of market surplus, the average total surplus decreases with the imposition of minimum wage. When the minimum wage increases the average total surplus decreases (from 60, 59 to 42 USD when minimum wage is below, at, and above equilibrium respectively).

[52] The average transaction price when the minimum wage is above and at an equilibrium level, and the market efficiency for all three levels of the minimum wage are significant at a 1 percent level. Here average contract wage has a unit of USD.

However, the S&D model shows that employment increases with an increase in the minimum wage. It is presented in the figure above as the average number of contracts per period is 1.3, 1.5, and 1.8 for the minimum wage below, at, and above equilibrium, respectively. Now these results contradict the theoretical predictions of the competitive equilibrium model but explain the empirical results in the labor market.

These results show that the successful number of contracts in the market with high search and high transaction costs is equal to the market with no friction. An increase in the employment level with an increase in minimum wage could be due to these market frictions that stop the firms from expelling and re-hire employees.

The same results are found in another variation of market friction i.e., low search and high transaction costs. The employment level increases even higher with an increase in the minimum wage.

With an increase in minimum wage, the average transaction prices move away from the equilibrium and the market efficiency keeps declining. The same phenomenon is depicted if look at the period-wise bid-ask spread and the successful number of contracts.

Table 6.10: Impact of minimum wage on employment (with low search & high transaction costs)[53]

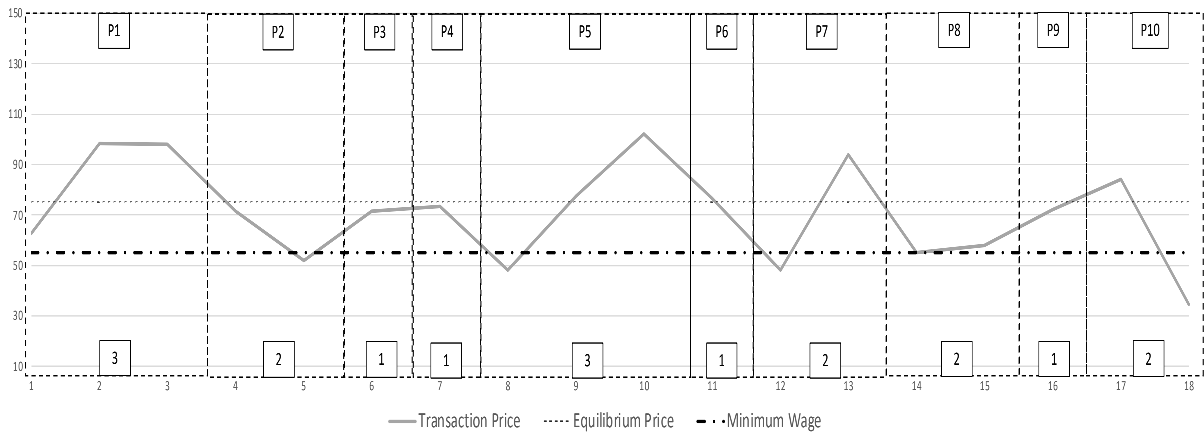
Min Wage	**Below Equilibrium**		**At Equilibrium**		**Above Equilibrium**	
Period	Avg. C.W	Efficiency	Avg. C.W	Efficiency	Avg. C.W	Efficiency
1	86***	27	99	11	111	11
2	62***	21	102	18	111	15
3	72*	9	109	13	103	12
4	74	18	106	25	102	5
5	76	29	101	15	104	6
6	77	7	107	15	107	10
7	71*	20	101	9	100	11
8	57***	15	114	9	113	9
9	72*	15	96	12	101	9
10	59***	12	105	12	114	11

Here, the level of significance is shown by *, **, and *** at 90%, 95%, and 99%, respectively.

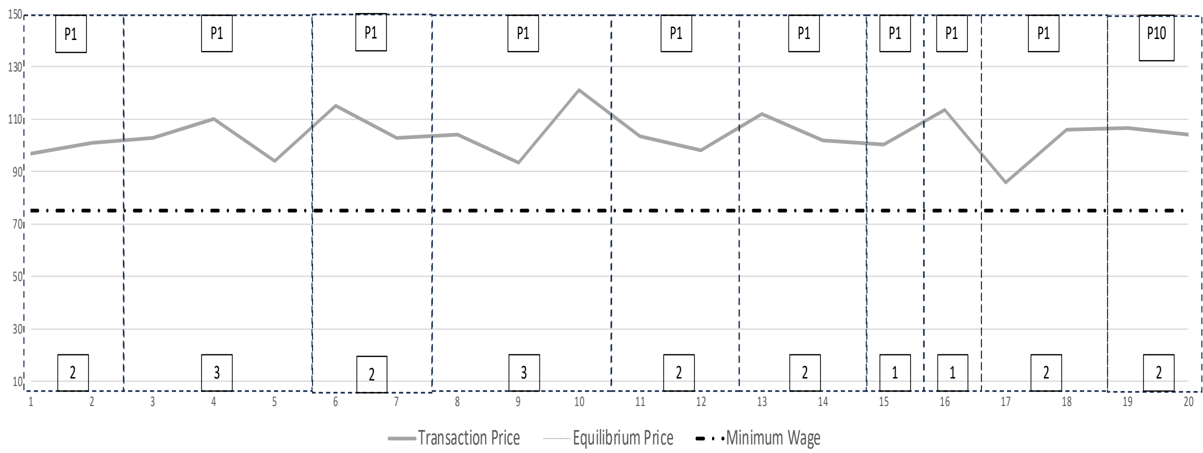
[Source: Author's own]

As the minimum wage increases from below equilibrium level to equilibrium and then above equilibrium, the total number of successful contracts or the employment level also increases from 18 to 20 to 22, respectively. This increase in the employment level is major because of the high transaction cost. Due high transaction cost involved in replacing the workers motivates the firms to not decrease the employment as they may have to face even higher costs in the future. This impact of increasing employment with an increase in the minimum wage is constant for low and high search costs.

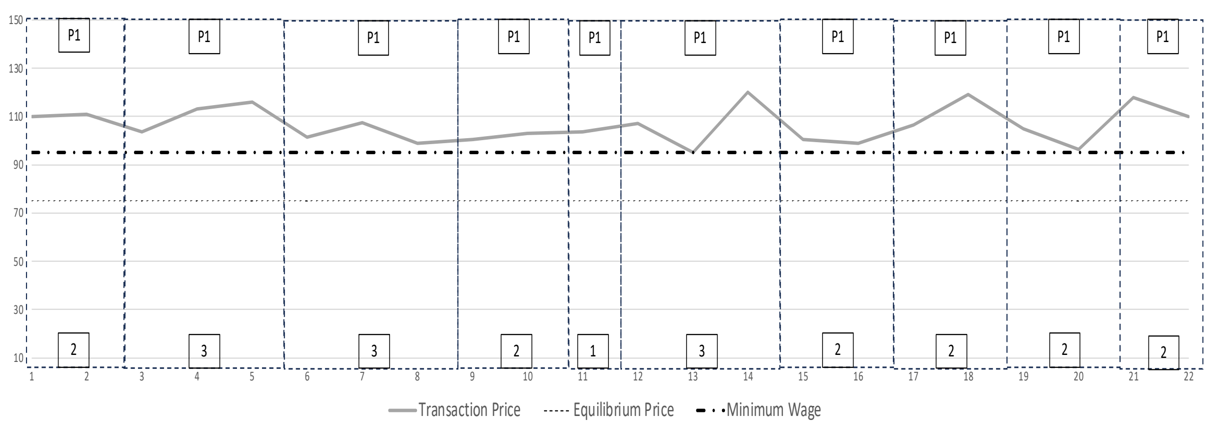
[53] The average transaction price when the minimum wage is above and at an equilibrium level, and the market efficiency for all the three levels of minimum wage are significant at a 1 percent level. The average contract wage is shown in USD.



Panel A: Minimum wage below equilibrium



Panel B: Minimum wage at equilibrium



Panel C: Minimum wage above equilibrium

Figure 6.9: Impact of minimum wage law on unemployment with low search and high transaction costs [Source: Author's own]

These results show that the minimum wage imposition can be helpful for the labor market as it causes an increase in employment. The next question is whether this increase in employment due to an increase in the minimum wage is still way lower than the theoretically predicted employment level. This question is answered in the next section which highlights the importance of measuring tools used to quantify the market performance. In the previous S&D model, the market efficiency is described in terms of the level of surplus gained from the contracts, although we also looked at the employment level. But an important aspect to consider here is how the S&D is constructed which leads to these results. The next aims to shed light on this angle of the S&D model.

6.2.3.3. Policy Lesson

An increase in the minimum wage doesn't always lead to a decline in the employment level, as described by the standard supply and demand model. However, it depends on the market structure along with other factors that support employment.

Competitive market theory predicts that any government involvement leads to market inefficiency and hence shall be discouraged. But here the results of this research propose that even with market frictions, government involvement can support the market by increasing efficiency.

In the real markets, frictions, in terms of search and transaction costs, are common to observe. It is because of these frictions that the minimum wage imposition proves to be helpful in the labor market to increase employment. For instance, with an increase in minimum wage, the living standard of the laborers can be increased without the cost of declined employment. It is because of the market frictions that the firms are incentivized to retain the workers even with increased minimum wage. It helps the policymakers to increase the living standards of the workers without facing the opportunity cost of increased unemployment in the labor market. In the labor market, with high market frictions, the government shall intervene in the market with an imposition of minimum wage laws so that the labor demand does not decrease, and employment level can be sustained.

6.2.4. Measuring Market Welfare

One of the main elements that affect market efficiency is how it is measured. In previously discussed S&D models, efficiency is measured by the level of surplus gained by all the market agents in the period. This is expressed as a percentage of the maximum theoretical surplus that can be gained. But this measure of efficiency ignores the efficiency of the labor market in terms of contract volume or employment efficiency, i.e., how many laborers got employed in a period as a percentage of the maximum theoretical employment level. In this section, the focus is more on the employment efficiency of the S&D model instead of surplus efficiency.

Now, in the case of surplus efficiency, we started from the baseline model while following the randomized trading sequence. The competitive market employability level in the market is considered equal to 10 contracts. But the surplus efficiency measure only considers the gain from the contracts but ignores the amount of loss caused due to unemployment. The disutility of workers who have not been able to find a job is considerably higher than the utility of workers who gain from the contracts. It means that the surplus measure doesn't incorporate or address the issue of the inability to capture the loss from unemployment. So, the efficiency of the S&D model shall not be compared with the competitive market theory as it underreports the maximum achievable employment level.

To address this issue, this study proposes another trading sequence that helps to attain market efficiency (in terms of employability) considerably higher than predicted by the competitive market theory. The trading sequence proposed here is called the Matching trading sequence. It states that the widely accepted Marshallian trading sequence provides efficient results in the labor market. It also states that only the intra-marginal traders can trade with each other and maximize the surplus. However, here the aim is not to maximize the surplus but to maximize employability in the labor market.

The matching sequence states that the laborers with the lowest ask prices should have an employment contract with the firm having the bid price just above the laborer's ask price. It means that the laborer with the ask price of 'x' shall trade with the firm having the lowest bid price (but higher than the ask price of the laborer).

Table 6.11: Contract volume efficiency in case of minimum wage imposition (low search & high transaction costs)[54]

Min Wage	**No Minimum Wage**		**Below Equilibrium**		**At Equilibrium**		**Above Equilibrium**	
Period	Avg. C.W	Efficiency (%)	Avg. C.W	Efficiency (%)	Avg. C.W	Efficiency (%)	Avg. C.W	Efficiency (%)
1	74*	160	82	140	94	100	107	60
2	75	140	86	140	86	120	105	70
3	75	170	78	130	92	100	105	70
4	76*	150	80	140	99	90	109	50
5	74*	160	80	140	88	110	109	40
6	74*	160	79	140	95	90	105	60
7	71***	150	80	150	94	110	104	70
8	77***	160	79	140	95	100	111	50
9	77***	160	79	140	96	100	103	80
10	76*	170	80	160	94	110	109	60

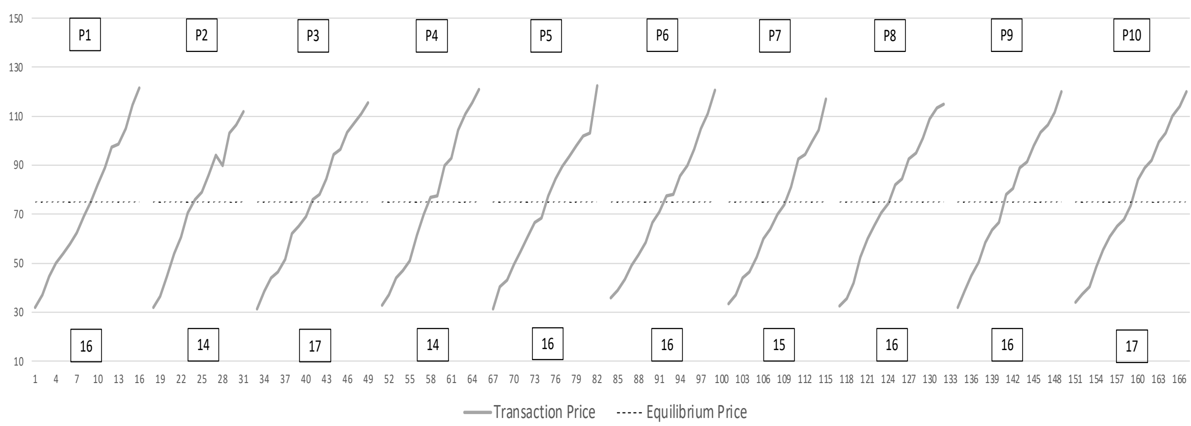
Here the level of significance is shown by *, **, and *** at 90%, 95%, and 99% respectively.

[54] The average contract price when the minimum wage is above and at the equilibrium level, and the market efficiency for all three levels of the minimum wage are significant at the 1 percent level. The average contract wage is provided in USD.

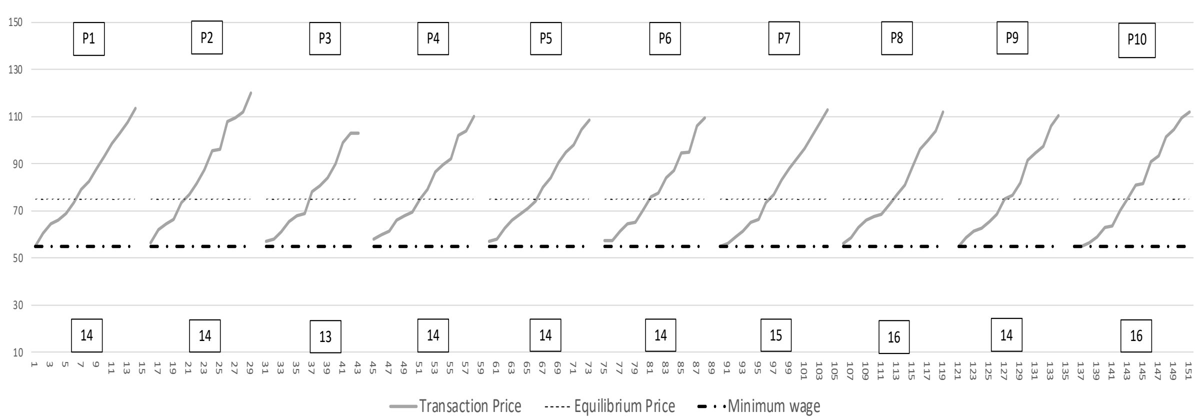
[Source: Author’s own]

Here two variants of market friction are introduced i.e., high and low transaction costs. The search cost is low in both cases because all the market agents are allowed to trade with the partner who is the closest match. It can be ensured either through labor unions who know better about the labor conditions or the government authorities who have information about the profit margins and paying capacities of the firms. It leads to lower search costs in the market framework. The result of these two cases with and without minimum wage impositions is presented here.

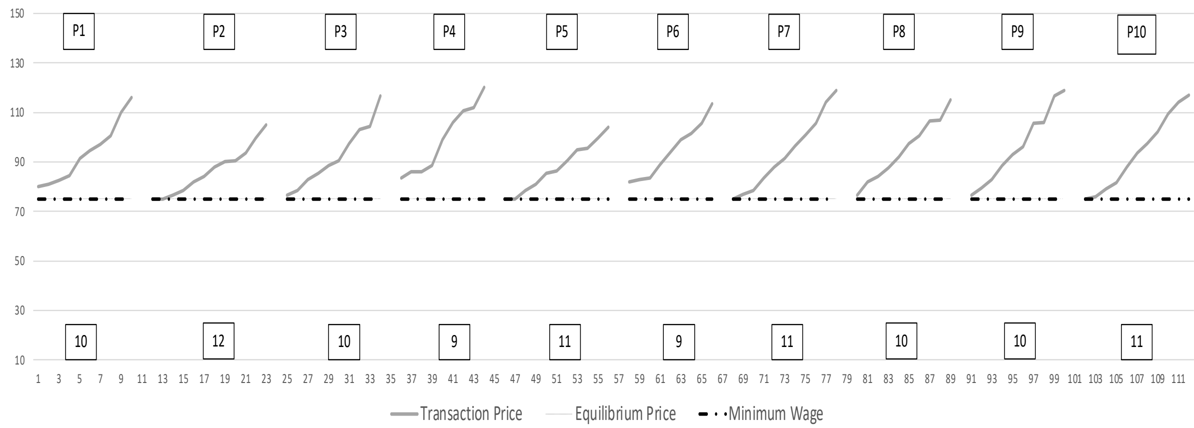
The details of these same results can be depicted in the figure below.



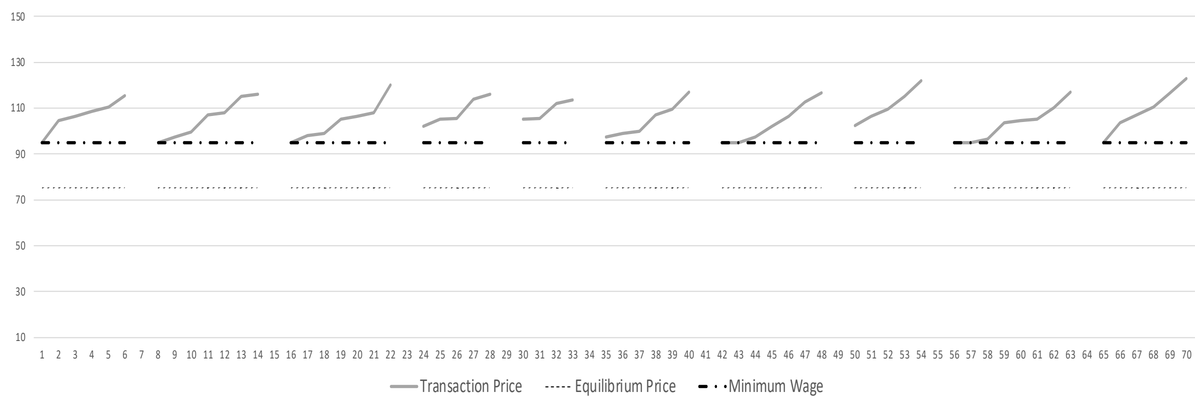
Panel A: No minimum wage



Panel B: Minimum wage below equilibrium



Panel C: Minimum wage at equilibrium



Panel D: Minimum wage above equilibrium

Figure 6.10: Market contract volume efficiency in the presence of minimum wage with low search and high transaction costs [Source: Author's own]

The results of the S&D model for the labor market populated by ZI agents with the applicability of matching trading sequence show that employment is far higher than the theoretically predicted employment level. With no minimum wage law, the total number of successful contracts is 158 as compared to 99 contracts (which is almost equal to the theoretically predicted contract volume) in

10 periods. The average contract volume per period is way higher than the competitive level i.e., 10 per period[55].

With the imposition of minimum wage law, the volume of contracts decreases as the minimum wage increases but still, it is higher than the employability with randomized trading sequence. The average per period employment efficiency is 158 percent with no minimum wage law. Then it decreases to 142 percent with the minimum wage below the equilibrium level. It further decreases to 103 percent with the minimum wage at the equilibrium level. Finally, it drops to 61 percent with the minimum wage above the equilibrium level. So, most of the time, the contract volume efficiency is significantly higher than the theoretically predicted volume. If the early results of the S&D model with high transaction costs are compared across randomized and matching trading sequences, it is evident that the matching trading sequence is more efficient. It helps to decline unemployment in the market with a high friction level.

6.2.4.1. Policy Lessons

These results are important in three ways. First, the market efficiency varies based on the measure used to calculate it. In the labor market, the more appropriate measure for the market efficiency is the contract volume efficiency. The reason is that it is more important for the laborer to get the job than the increase or decrease in the surplus. So, the surplus efficiency shall not be used in every market as done in the literature. The policymakers shall rely on the volume efficiency in the labor market while ensuring the full employment rather than focusing on maximizing the surplus.

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[55] The simulation results for low search and low transaction costs show the same market outcome with lower employability. These results exhibit that market frictions are not always bad for the market but sometimes they provide positive signals in the market as they lead to more job security, higher skills or potential of the laborers, loyalty of employer with the workers, and the trust between them.

Even with high market frictions, the labour market can have employment above the theoretically predicted level of employment. So, market frictions are not always bad but sometimes it motivates the market participants to act in the direction to enhance the market efficiency. For instance, due to high market frictions, the search and transaction costs increased and firms have to retain the workers even with higher minimum wage imposition. So, the government shall consider applying the minimum wage laws without facing the opportunity cost of employment level in the economy.

Government involvement in the labor market doesn't always lead to market inefficiency and the market itself doesn't always produce efficient outcomes if left free to work. For instance, if the government ensures a low information cost in the market, then the market efficiency may increase even with high transaction costs. So, the policymakers must focus more on the access of information to the laborers and the firms while ensuring low-cost information. It will help them to explore the best option while choosing the firm or the laborer but with transaction costs the firms are discouraged from replacing the workers. It ensures the employment level in the economy.

Here the emphasis is that the qualitative results would not change – fixing prices (minimum wage) would not be always inefficient – all alternative structures would provide better approximations to the real world than the original S&D model, which does not consider information and transaction costs. What we have shown is that to get closer approximations to reality, the specific details of the information and transaction costs (microstructure) matter for how the market operates.

6.3. Recommended Policy Takeaways

In summary, the policy recommendations aim to balance the goals of increasing the living standards of workers through minimum wage increases while considering potential market frictions. A nuanced and well-considered approach that addresses the specific needs and challenges of the labor market can contribute to positive outcomes for both workers and businesses.

Context-Specific Minimum Wage Policies:

Tailor minimum wage policies to the specific characteristics of the labor market, considering the market structure and factors that support employment. Recognize that a one-size-fits-all approach may not be suitable, and policy adjustments should align with the unique dynamics of each market.

Reevaluation of Competitive Market Theory:

Challenge the blanket application of competitive market theory that discourages any government involvement. Acknowledge that, contrary to theoretical predictions, government involvement, even in the presence of market frictions, can enhance market efficiency. Consider a nuanced approach that recognizes the potential benefits of targeted interventions.

Acknowledgment of Common Market Frictions:

Acknowledge the prevalence of common market frictions, such as search and transaction costs, in real markets. Instead of viewing frictions solely as impediments, recognize them as inherent features that can be leveraged to improve market dynamics.

Minimum Wage Imposition as a Tool:

View minimum wage imposition as a tool to address market frictions and increase employment. Understand that, in the presence of search and transaction costs, a well-designed minimum wage policy can be instrumental in enhancing the living standards of laborers without causing a decline in employment.

Incentivizing Worker Retention:

Recognize the role of market frictions, particularly search and transaction costs, in incentivizing firms to retain workers even with increased minimum wages. Understand that these frictions can contribute to the stability of the workforce, reducing turnover costs and supporting overall market efficiency.

Policymaker's Opportunity to Increase Living Standards:

Empower policymakers to use minimum wage adjustments strategically to increase the living standards of workers. Leverage the opportunity to enhance the well-being of laborers without incurring the opportunity cost of increased unemployment, particularly when market frictions are present.

Reconsideration of Market Efficiency Measures:

Policymakers should recognize that market efficiency in the labor market is contingent on the appropriate measure. Contrary to using surplus efficiency, focus on contract volume efficiency as a more relevant measure for assessing labor market efficiency. This shift in measurement can provide more accurate insights for policymaking.

Consideration of Frictions as Motivators:

Acknowledge that market frictions, even when high, can lead to employment levels surpassing theoretical predictions. Understand that frictions may not always be detrimental; in some cases, they motivate market participants to take actions that enhance overall market efficiency. Policymakers should consider the potential positive effects of friction in certain contexts.

Nuanced Perspective on Government Involvement:

Challenge the notion that government involvement in the labor market invariably leads to inefficiency. Recognize that a laissez-faire approach doesn't always produce efficient outcomes. Instead, understand that targeted government interventions can enhance market efficiency. For example, reducing information costs can improve efficiency even in the presence of high transaction costs.

These policy takeaways emphasize the importance of context-aware policymaking, challenging conventional economic theories when necessary, and leveraging market frictions as opportunities rather than obstacles. They underscore the potential for well-designed minimum wage policies to simultaneously enhance the well-being of workers and support overall labor market efficiency.

These takeaways are important to recognize the dynamic nature of the labor market and the potential positive roles of both government intervention and market frictions in shaping outcomes.

6.4. Theoretical Implications

The theoretical implications underpin the importance of how these results contribute to the microeconomic theory of market efficiency in terms of providing evidence related to market microstructure. This strand of microeconomic theory is well-researched through the tools of experimental economics and agent-based modeling. How important the importance of microstructure in reaching the desired results is not well documented in the literature. This research tries to fill this gap by introducing new details of market microstructure in artificially simulated markets that mirror human experiments. The theoretical and policy implications of the research results are presented below.

Theoretical implications of this research results are expedient to understand the factors affecting the market performance. The results of this research imply that market efficiency is dependent on the selection of market microstructure. The details regarding how the market is set up are important to consider for the markets to provide efficient outcomes. It is not the case that markets are universally efficient as it was thought by looking into the results of artificially simulated ZI-populated markets. The assumption of competitive market theory matters to provide an efficient market outcome.

The general conception of market efficiency is not as true as it was thought to be. This is irrespective of the rationality of participants, the availability of information, the number of buyers and sellers, the learning behavior of participants, and the market trading mechanism. These factors affecting the market performance and required to be considered are detailed below.

6.4.1. Rationality of Traders

From the initial results of ZI-populated artificially simulated market results, it is contemplated that the markets are always efficient even without the rationality of traders. ZI-agent provides results in line with the market performance while controlling the rationality assumption. It is then thought that the markets are perfectly competitive and do not need their participants to be rational.

However, the results imply that this understanding is vague, and more work is required in this direction. High allocative efficiency in the absence of human traders does not mean that markets do not need rationality to be efficient. But the result of high allocative efficiency is because of other market settings i.e., the market trading sequence.

6.4.2. Learning Mechanism

Like rationality, the earlier results of ZI-populated markets enforce market efficiency in the absence of any learning mechanism. Afterward, the market populated with ZI agents having some learning mechanism come up with better results as compared to no-learning ZI agents. It opens new avenues of the important impact of learning in market performance. A market populated with ZI agents doesn't always lead to efficiency, but it again depends on other details of the market.

This research illustrates the importance of learning mechanisms to improve the efficiency of ZI agents. But still, market efficiency is not influenced by learning, but it is also important that what are the learning rules, how the trades happen, what demand and supply schedules are set, and how bid and offer prices are shouted. So, learning is one of the major factors affecting market efficiency, and ignoring it compromises market performance.

6.4.3. Trading Sequence

Generalizability of market outcome is any kind of market setting while relaxing the assumption of the competitive market theory is well established after the results of a ZI-populated simulated market. However, these results are only possible with the Marshallian trading sequence as it ensures allocative efficiency. If the Marshallian trading sequence is substituted with any other trading sequence, then the results of the same ZI-populated artificial market are changed.

For instance, when the Marshallian trading sequence is switched with a Randomized trading sequence then the trade volume efficiency remains the same, but the allocative efficiency decreases significantly. Similarly, if the market aims to maximize the trade volume efficiency, then Reverse Marshallian Sequence should be implied. All these trading sequences are assumed to reflect the real-world market. The best way to adopt the trading sequences is to look into the trading sequence that serves well-being. This should be done without generating economic inequality and ensuring inclusiveness. Hence, the trading sequence is an important element of market microstructure that has a significant impact on market efficiency.

6.4.4. Demand and Supply Schedules

Like other details of market microstructure, the importance of demand and supply schedules cannot be ignored either. Literature shows market efficiency with human as well as ZI-populated markets when the demand and supply schedules are constant over the periods. But in real markets, these demand and supply schedules keep changing continuously as new buyers and sellers come in and others go out.

The constant dynamic nature of real markets is not mirrored in experiments and simulated agent-based models. For this reason, it is imperative to reconsider the results of experiments and simulated markets with changing demand and supply over the periods along with alternative trading sequences.

6.4.5. Simplified Learning Models

In the ZI-populated market, having agents with learning abilities, complex kind of learning mechanisms are assumed. The purpose of assuming these complex learning mechanisms in the literature is to impersonate the real-world learning of human traders and to come up with such a learning mechanism that provides the highest allocative efficiency. It is the reason that most of these learning mechanisms used in artificially simulated markets have very less resemblance to an actual process of how humans learn about the market.

For this reason, instead of implying a complex and unrelated type of learning mechanism, an effort should be put into diagnosing the performance of artificially simulated markets with an actual learning mechanism. It can be done by asking the traders about their decisions during the trading process on how and what they learn about the market. Then the learning rules can be extracted from these actual learning processes of human traders and can be applied to a simulated market to check the performance while controlling the other factors.

6.4.6. Range of Shouts

In an artificially simulated market, the same demand and supply schedules are used for human-populated markets to compare the market performance. Still, there are some elements to consider that are not present in the human-populated market. One of these is the range provided to agents to select their shout prices.

Selection of bid and offer price within the constraint is not an issue for the human-populated DA market as the traders shout the prices as per their market understanding. But ZI agents, who don't possess any rationality and decision-making mechanism, need some decision rules to follow for this purpose. Usually, a constraint is given to all buyers and sellers i.e., buyers have some minimum value below which they cannot select the bid price and sellers have maximum value above which they are not allowed to select the ask price. These ranges are important in artificially simulated markets because shouts are selected randomly within these ranges. An increase or decrease in these ranges may affect the shout prices in the simulated markets. Hence, these ranges and the selection of shouts from them tend to impact the overall market outcome. This is why the selection of these ranges is important and shall be selected based on experiments instead of choosing arbitrarily.

6.4.7. Selection of Transaction Prices

The process of transaction price determination is an important feature of market microstructure. In literature, most of the experiments and the agent-based simulated markets follow the rule that the transaction price is each trade equal to the shout price of the trader who enters the market first. But there are some markets where the transaction price is determined with some different mechanism. There can be many ways to decide about the transaction price. For instance, one of the ways can be the average of shouts of both buyer and seller. This way the transaction price is determined while assuming equal negotiation power for both sides of the market. Another way to find the transaction price can be the shout price of the trader who enters the market late while taking the shout of early entrant as given. Or the transaction price can be a random price between the shouts of both buyer and seller.

These processes of transaction price selection are important. Following different mechanisms of transaction price selection will ultimately impact market efficiency. This includes all its measures, i.e., allocative efficiency, volume efficiency, and price convergence.

6.5. Future Research Implications across the Globe

The S&D model has applications in every market. A large number of markets comprises of double auction market framework where the market phenomenon can be fully explained by S&D theory. It's because of the efficient allocation of resources as predicted by the S&D model that most of the market frameworks are inspired by it in the real world. The future implications of this research can be used in explaining the price formation and can be mirrored in any market like currency exchange, stock exchange, or other trading markets. There are countless future implications of the S&D model with alteration in market microstructure, but here we highlight few of them in the general context at the global level[56].

6.5.1. Start of Day Stock Price: Implication of Trading Sequence

[56] Here the S&D model is applied in the double auction market and its applications are considered so the policy implications and the applications are also in the context of the DA market while mirroring the implications of the S&D model.

Market efficiency depends not only on the behavior of traders but also on how the markets are set up. For instance, at the start of the day, to announce the beginning of the day stock price – which is different from the closing price on the last day – the Walrasian market mechanism is adopted. The first 15 minutes at the start of the day are allocated to determine the starting price in the market[57]. This finding of the starting price mechanism is one variant of the Walrasian auctioneer market framework. In general, the Walrasian market, as the first step, gathers all the shouts (bids and asks) and sets a price that provides the highest allocative efficiency while following the Marshallian trading sequence[58]. But here in the case of the stock market, an alteration is made in it by changing the trading sequence in the Walrasian market. Although the stock exchange plays the role of Walrasian auctioneer for the first 15 minutes but doesn't follow the Marshallian trading sequence as its purpose is not to maximize the allocative efficiency. So, what happens is the trading price is set at a level where maximum trades are executable. To serve this purpose, all the bids and asks are allocated in a Reverse Marshallian sequence[59]. This trading sequence serves the purpose opposite to the Marshallian trading sequence. Where the Marshallian trading sequence is helpful in maximizing the profit for all traders in the market, the Reverse Marshallian sequence is useful in maximizing the number of executable trades between the traders. The purpose of the first it to

[57] In all the stock exchanges around the world, the first 15 minutes are allocated to find the start-of-the-day price for each stock in the market. This purpose is fulfilled by dividing these 15 minutes into three segments. The first 7 to 8 minutes (order collection period) are allocated to gather all the bid and ask prices from all the buyers and sellers. Afterward, in the next 4 to 5 minutes (order matching period), all the bid and ask prices are set in a way that a maximum number of trades can be done at any specific price which is set as transaction price. The last 3 to 4 minutes (buffer period) are then spent to announce the start of the day price in the market.
[58] In a simple Walrasian market, all bids and asks are gathered and a single price is found at which maximum surplus can be attained. It is achieved by arranging bids in descending and asks in ascending order and then match the traders so each of them can gain maximum possible surplus.
[59] The reverse Marshallian trading sequence arranges the trades in an order that is opposite to Marshallian trading sequence. Here, the bid of buyers is arranged in ascending and ask of sellers are arranged in descending order. Then trade happens between the buyer of lowest possible bid price and seller of lowest possible ask price.

maximize the allocative efficiency (surplus) and the second serves to maximize the number of trades.

It leads to the conclusion that the trading sequence is important to get the desired market outcome. At the start of the day, the market makers want to find the price at which trade volume efficiency can be maximized so they follow the Reverse Marshallian sequence. But during the normal daytime, the purpose of the market is to provide a high possible surplus to the traders, and the market is set to follow the Marshallian trading sequence. It shows that the market outcome and its performance are subject to the type of trading sequence that is to be used in the market. Similarly, if a Randomized trading sequence is to be used then allocative as well as trade volume efficiency could be compromised but the matching of all the traders will be done entirely on a random basis.

It leads to conclude that the market by itself is not efficient as shown in earlier experiments. Markets are also not unconditionally efficient in always providing maximum surplus irrespective of the rationality of individuals and their learning abilities as presented in artificially simulated ZI-populated markets. However, the market outcome depends on many factors, generally known as market microstructure. It is the market microstructure that ensures the kind of results we want markets to provide us. So, the general perception of markets to be efficient – if left free to work on their own – is not true as illustrated in DA experiments and ZI simulations. Price convergence, allocative efficiency, and trade volume efficiency of the market vary with altering market microstructure.

6.5.2. Market Microstructure and Stock Market Efficiency

The efficiency of any auction market, like of stock market, is thought to be dependent on the availability of information, supply and demand structure, transaction cost, and many other information variables[60]. Once the start of the day price is announced in the market the trading is then moved to follow the normal market mechanism. During the whole day, the transaction takes place following the Marshallian trading sequence. We conclude that the Marshallian trading sequence alone is only one of the many particulars of the market microstructure. Other minutiae include the demand and supply schedules, bid and ask spreads, availability of information, transaction cost, the rationality of traders, and so on. The purpose of the stock market is to provide the maximum allocative efficiency and it is ensured by following the Marshallian trading sequence. But, as described earlier, only following the trading sequence does not guarantee allocative efficiency. As the results described, the efficiency of the market is contingent on the microstructure. Altering the trading sequence leads to different results similarly changing the other details also affects the market performance.

The theoretical viewpoint of efficient performance of markets irrespective of all the details (rationality, information, market forces, transaction cost, learning behavior, and trading sequence) is not found to be true. It is the reason that stock markets may follow different forms of microstructures depending upon their desired results. If they want to achieve high trade volume efficiency, the focus is on the Reverse Marshallian trading sequence but if the focus is to provide high allocative efficiency, then the most eligible candidate is the Marshallian trading sequence. Similarly, if the goal is to provide market efficiency in terms of the unpredictability of prices, then the most suitable candidate can be the Randomized trading sequence. The most appropriate

[60] The Efficient Market Hypothesis (EMH) illustrates that markets are not efficient if no investor can earn an abnormal return in the market, and it is possible only when all the investors have equal access to information. The efficiency in the case of EMH is in terms of equal opportunity to make a profit to all the market participants. But here the term efficiency does not incorporate the inequality measure but only focuses on gaining maximum from trades.

example of the stock market with the DA market framework in today's world are New York Stock Exchange (NYSE)[61].

6.5.3. Energy Trading Market

Recently, to make the energy market private and decentralized around the world, the double auction framework is used. The purpose of using the double auction framework is its high level of efficiency along with market competitiveness. Electronic trading platforms have been made available very recently in this context.

For instance, a mobile application with the name P2P Energy Trading is introduced in developed economies where households can buy energy and producers can sell it online. Here the price is set through auction. But this specific type of energy market is not a continuous DA market as half of the day is allocated to buyers to make the bid and during the remaining half of the time, sellers make their offer. Again, the Marshallian sequence is followed to determine the transaction price.

Due to its wide-scope application, the use of the double auction market is increasing speedily with the privatization of the energy market, especially in Western economies.

6.5.4. Resource Allocation Grids

Allocation of resources between buyers and sellers is now being managed efficiently through online DA markets. One of these types of resource allocation is the cloud market where the sellers offer to sell the cloud storage to the buyers online through websites or mobile apps. This market is working efficiently as many sellers enter the market to sell cloud storage. These products are homogeneous with varying quantities and prices as we have in the DA market framework.

[61] The NYSE started its operations in hybrid form and still provide the market framework oral double auction.

Like the other markets, the exchange grid works as an auctioneer that helps to match the bids and asks of buyers and sellers respectively. The Marshallian trading sequence is enforced in these types of markets. One of the major differences in these resource allocation grids is that the service providers or sellers of the cloud services ensure their service which is time constrained. If the sellers are unable to sell their services in the resource allocation market, then their unsold resources got wasted. Similarly, cloud service buyers also face a time constraint as they must complete their tasks within a limited time and need cloud services for that specific period. It ensures pressure on both sides of the market as it is in the case of human-populated DA experiments. How these time constraints are to be embedded in the ZI-populated simulated markets still needs sophisticated algorithms and more efforts are required in this direction.

6.5.5. Secondary Vehicle Market

Another major implication of DA market efficiency is seen in its applicability in the auction market for auto vehicles. The buyers and sellers can trade the autos and even their parts online through a website[62]. This auction market uses the Marshallian trading sequence if more than one trader is eligible to trade. The results of this research regarding the importance of learning and market microstructure are important to consider for the efficient allocation of resources and better market performance.

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[62] An example of such an auction market is Copart which provides an online platform for buyers and sellers through a website. More than 175,000 vehicles are listed on Copart and it's operating in 11 countries now. However, its market framework is different from the DA market that we discussed in simulations and theory. Here buyers can improve their bids at time for the price posted by the seller and if the seller agrees then the trade will go through otherwise sellers have to wait for upcoming bids. On the seller's side, they can also improve or revise their offer price once they observe a change in demand or bids by the buyers. Another difference in the online vehicle auction market is that the goods available to trade are not homogeneous as assumed in the theory. So, the element of heterogeneous goods with limited information available needs to be accounted for in this market and, for this purpose, more research is required.

The major difference between this type of online marketplace and the theoretical result from the simulation is the variation in goods available to trade. It is because of the difference in types of goods available for each trade that the assumption of homogeneous goods in the market is not fulfilled here.

6.5.6. Industrial Equipment Auction Market

There is now an online market for the auction of industrial, commercial, plant, and machinery equipment through an online marketplace. Here, sellers are authorized companies only that deal is the same as well as differentiated products. There are more than 350 authorized sellers who come up to sell their products either to individual buyers or to companies. One of the major differences concerning simulated markets discussed earlier is the sequence of announcing the offer and bid prices. Sellers are going to offer the price first and buyers are going to bid for it. Although sellers can improve their offer price while witnessing the shout prices of buyers at one point in time the offered price is announced and remains fixed until the product is purchased by the buyer, or the seller revises the offer.

This type of market doesn’t follow the Marshallian trading sequence. The reason for this is the posting of prices by the seller first and then buyers compete for it. But other details of the DA market still impact market efficiency. These include the learning mechanism, the type of demand and supply schedules, variation in demand and supply, and the availability of information about the product. These factors continue to play a role in the DA market framework.

6.5.7. Derivative Market

The derivative market is used to manage the uncertainty and future risks following the DA market framework which happens in NYSE. The most famous example nowadays is the Chicago

Mercantile Market which offers a marketplace to buyers and sellers of derivatives like Futures, Swaps, Forwards, and Options. These derivative markets keep on the auction market open outcry system. Although the NYSE was converted from strictly operating on the auction market to a hybrid market in 2007 whereas Chicago Mercantile market still uses the DA market framework.

The learning process of agents is an important feature in making abnormal gains from the market as they use heuristics to account for future uncertainty and make gains from it. The Marshallian sequence of trading is used here but the market performance and its allocative efficiency depend on factors like learning mechanism, information availability, and rational decision-making of individuals. So, like other markets, the derivative markets, having a DA market mechanism, may not provide an efficient outcome as predicted by economic theory while ignoring the market microstructure.

CHAPTER 7

CONCLUSION

Competitive economic theory implies market efficiency and its generalizability in all situations. The theory predicts that the competitive market leads to price convergence towards equilibrium, provides maximum attainable surplus, and has the highest trade volume. These predictions of competitive economic theory are based on assumptions of the market to be competitive. Competitive markets provide these predicted outcomes when some specific assumptions are ensured. These assumptions of a competitive market are the rationality of traders, availability of full information, no transaction cost, and many buyers and sellers.

To support these theoretical vistas of basic economic theory, experimental economics comes up with surprising results that show the double auction market leads to outcomes as predicted by economic theory. These experimental results are robust with the low number of participants and availability of partial information to them. These results of human experiments are not conditional on the type of demand and supply schedules in the market. In the context of human experiments, the double auction markets are thought to be efficient as predicted by economic theory.

The results of double auction markets are found to be in accordance with the economic theory even when some assumptions of competitive economic theory are relaxed. It is then thought that other assumptions of economic theory like rationality, learning of traders, and information availability can also be examined to test the market efficiency.

To test the assumption of rationality the human learning behavior must be controlled. This purpose is achieved by imitating the double auction market framework in an artificially simulated market with superficial agents known as ZI agents. The specialty of these ZI simulated agents is that they don't possess any intelligence so are not rational and don't learn anything about the market. The replication of the DA experimental market with these ZI agents helps to control the assumption of rationality while examining the market efficiency. The results of the DA market with these ZI-populated artificial markets also lead to market efficiency in terms of high allocative and volume efficiency but don't exhibit convergence of transaction prices. These results state that the rationality at individual level is not required for the agents to offer market efficiency. In contrast, the market mechanism is efficient enough to lead to efficiency. In other words, the invisible hand working in the market is strong enough that it even doesn't require the agents to behave rationally. Only if the market microstructure is set up according to the DA market does it provide an efficient outcome. This occurs even in the absence of rationality, with a small number of buyers and sellers, and with limited information available.

The initial results of an artificially structured ZI-populated market follow the Marshallian trading sequence i.e., one of the important elements of market microstructure. We here try to find out the importance of following such a specific trading sequence as if it is the reason for market efficiency or the markets are efficient even when any other trading sequence is followed. For this purpose, a new kind of trading sequence is introduced in an artificially simulated market of ZI agents. In this new trading sequence, randomness is ensured at three levels: selection of agents to enter the market, selection of shout prices, and selection of agents to trade with each other. In the Marshallian trading sequence, randomness is ensured in the first two phases but in the third phase. This alternative trading sequence is known as the Randomized trading sequence.

With the introduction of a Randomized trading sequence, the DA market with the same microstructure is programmed in Python. Its results are less efficient than the results of the ZI market with a Marshallian trading sequence. It exhibits that the DA markets are not always efficient in the absence of rationality, but it depends on the way how the market is set up and what kind of microstructure is followed. So, the details regarding the market microstructure matter a lot, and changing these details the desired results can be attained in DA market with the ZI agents. The earlier convention of market efficiency with ZI agents is not independent of rationality.

These results motivate us to dig deeper into the process that leads to market efficiency by going one step ahead. Literature shows that if ZI agents are provided with some kind of learning mechanism or rationality then the market performance is enhanced significantly. These results are achieved by following the same Marshallian trading sequence along with installing some learning mechanisms for the ZI agents. The ZI agents while having the learning mechanism (ZIP agents) lead to even higher market efficiency in terms of higher surplus, greater trade volume, and convergence of prices towards the equilibrium. The major difference between the performance of ZI agents and ZIP agents is the convergence of prices as the convergence doesn't happen in the simulated market with ZI agents.

These results shed light on the importance of learning and rationality as it is necessary for the markets to be efficient, and it also clears the market at a price level that is close to a competitive equilibrium price. Here the issue witnessed is that the learning rule that is employed on the ZIP agents doesn't mirror how humans learn about the market. But this learning mechanism is assumed that provide an efficient market outcome. So, instead of taking the learning rules from human experiments, the rules lead to efficient results but are not practical. For this reason, this reason extracts the learning rules from the human experiments, and the agents that possess these learning rules are named ZIP_H agents.

First, these ZIP_H are involved in a market having a Marshallian trading sequence and then the trading sequence is switched to Randomized trading. Based on these new learning rules the market outcome again shows higher efficiency when compared with the ZI-populated market. The market with a Randomized trading sequence is a little less efficient than the Marshallian trading sequence in the presence of ZIP_H agents.

The results of the agent-based model show that the market microstructure plays an important role in price convergence and market efficiency. The market outcome is sensitive to the kind of trading sequence, type of demand and supply schedules, information available to the agents, and the learning mechanism assigned to the traders. The efficiency of competitive markets is not a universal phenomenon. It is not irrelevant to the market details. Each of these details plays an important role. They help the market achieve an outcome close to the theoretically predicted outcome. So, the market microstructure shall not be ignored as changing the microstructure may lead the market toward efficiency or move away from the theoretically predicted outcome of competitive markets.

Furthermore, this research aims to highlight the implication of the S&D model in the real-world market. Although they strike a balance between elevating workers' living standards through minimum wage increases and navigating potential market frictions. An approach that is nuanced and thoughtful, addressing the unique needs and challenges of the labor market, can yield positive outcomes for both workers and businesses.

A reconsideration of competitive market theory is proposed, challenging its blanket application that discourages government involvement. Contrary to theoretical predictions, this suggests that targeted government interventions, even in the presence of market frictions, can enhance efficiency. A nuanced perspective recognizes the potential benefits of tailored interventions.

Acknowledging the prevalence of common market frictions, such as search and transaction costs, is crucial. Rather than viewing frictions solely as impediments, they should be recognized as inherent features that can be leveraged to improve market dynamics. Minimum wage imposition is presented as a tool to address market frictions and boost employment. Understanding that well-designed minimum wage policies can enhance laborers' living standards without causing unemployment, especially in the presence of search and transaction costs, is essential.

Policymakers are empowered to strategically use minimum wage adjustments to increase workers' living standards. This opportunity should be leveraged to enhance laborers' well-being without incurring the opportunity cost of increased unemployment, particularly when market frictions are present.

A reconsideration of market efficiency measures is advocated, emphasizing the importance of contract volume efficiency over surplus efficiency in assessing labor market efficiency. This shift in measurement provides more accurate insights for policymaking.

A nuanced perspective on government involvement challenges the notion that it invariably leads to inefficiency. Recognizing that a laissez-faire approach doesn't always produce efficient outcomes is important. Policymakers should understand this. They should also recognize that targeted government interventions can help. For example, reducing information costs can enhance market efficiency. This can be effective even in the presence of high transaction costs.

These policy takeaways underscore the importance of context-aware policymaking, challenging conventional economic theories when necessary, and viewing market frictions as opportunities rather than obstacles. They highlight the potential for well-designed minimum wage policies. These policies can simultaneously enhance worker well-being and support overall labor market efficiency. They recognize the dynamic nature of the labor market. They also acknowledge the positive roles of government intervention and market frictions in shaping outcomes.

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Appendix

Appendix-1: Buyer's Redemption Values and Seller's Cost (Cliff and Bruten, 1997)

Buyer ID	Demand	Seller ID	Supply
1	325	12	75
2	300	13	100
3	275	14	125
4	250	15	150
5	225	16	175
6	200	17	200
7	175	18	225
8	150	19	250
9	125	20	275
10	100	21	300
11	75	22	325

Appendix-2: Description of Zero-Intelligence Plus Agents by Cliff and Bruten (1997)

Similar to ZI agent populated market of Gode and Sunder (1993), the microstructure of ZIP populated agent also works under the Marshallian sequence. So, the whole market mechanism is same except the condition applied on the agents to learn from their surroundings. In ZIP populated market, agents are allowed to learn from the other traders and improve their shout prices accordingly.

1. Allocate limit prices (i.e. redemption values and costs to buyers and sellers) given already by the experimenter.
2. Allocate the profit margin for buyers and sellers that is in the range of 5% and 35%. This profit margin is randomly selected from this range to start the experiment in period-1 and remains fixed for 10 periods. With these allocated profit margins, the initial shout prices are calculated for all the traders.
3. Randomly any one trader (buyer or seller) is selected from the list of all traders. This process keeps repeating until at least 1 buyer and 1 seller is selected.

4. Transaction condition: If the shout price (bid) of buyer >= shout price (offer) of seller then the trade will happen between the two at shout price of trader who enters the market first.
5. When the trade will happen, both buyer and seller will become inactive as now they can learn about the market and improve their shout price accordingly but cannot involve in the transaction.

For the learning purpose, the

ZIP-agent use the market response and observable activity of other agent in the market to update its profit margin with each passing trade. ZI-agents adapt their price using the Widrow-Hoff rule each time they hear a shout from another trader in the market. This rule includes learning rate which influence how quickly an agent can learn. Cliff and Bruten defines this learning rate to be random number from a uniform distribution [0.1, 0.5]. So, every ZIP trader is learning positively with each passing trade. Then there is a random momentum value drawn from a uniform distribution [0.2, 0.8]. If the agent had a successful (unsuccessful) transaction in the previous round, it then increases (decreases) the profit margin.

Set of rules for ZIP by Cliff and Bruten (1997):

i. ZIP Seller has following set of rules.

   If the last shout is accepted at price q[63]:

   a. If last shout is an ask price, any seller who asked a price lower or equal to last transaction price (q), raises its profit margin in current period.
   b. If last shout is a bid price, any seller who asked a price higher or equal to transaction price lowers its profit margin in current period.

   Else:

[63] Here ‘q’ is the transaction price.

a. If last shout is an ask price, any seller who asked a price higher or equal to q lowers its profit margin.

ii. ZIP Buyer has the following set of rules.

If the last shout is accepted at price q:

a. Any buyer who bid a price higher or equal to transaction price, raises its profit margin in the current time period.

b. If the last shout is an offer, any buyer who asked a price lower than or equal to transaction price, lower its profit margin.

Else:

a. If last shout is a bid, any buyer who asked a price lower than or equal to q, lowers its profit margin in current period.

The profit margin is updated using the Widrow-Hoff with momentum learning rule:

$$\Delta_i(t) = \beta_i * (\tau_i(t) - p_i(t))$$

Here 'ß' is learning rate, 'p' is shouting price of agent, and 'τ' is target price calculated based on recent submitted shout price. After the trader observes any submitted shout, it updates its profit margin 'μ' according to following equation.

$$\mu_i(t+1) = \frac{p_i(t) + \Gamma_i(t+1)}{l_i - 1}$$

with 'l_i' representing the trader's limit price and '$\Gamma_i(t+1)$' being calculated through following equation.

$$\Gamma_i(t+1) = \gamma_i(t) + (1 - \gamma_i(t)) * \Delta_i(t)$$

where 'γ_i' represents the so-called momentum coefficient. Finally, when the trader submits a shout at time 't' it will calculate a shout price through equation.

$$p_i(t) = l_i * (1 + \mu_i(t))$$

For ‘β’, each trader generates a random value from a uniform distribution U (0.1, 0.5).

‘γ’ is randomly generated for each trader from a uniform distribution U (0, 0.1).

‘μ’ is randomly generated for each trader from a uniform distribution U (5%, 35%).

‘c’ is perturbations that also randomly generates a value for each trader from a uniform distribution U (0, 0.05).

All participating traders have a limit price, in this scenario again randomly generated from a uniform distribution U (0.75, 3.5).

6. All the ZIP agents, whether active or inactive, learn about the market with the learning rules describes above. In the subsequent periods, the profit margin is updated but all the agents start with same shout prices as used in the last trading period. So, ZIP traders keep learning across the trading periods and this learning process does not stop even if they are inactive or not involved in trading as they can still observe what’s happening in market.

[Source: Cliff and Bruten, 1997]

Appendix-3: Labor demand and supply elasticities

Study	**Elasticity**	**Value**
Amodio and Roux (2021)	Labour Supply	2.5
Hershbein (2020)	Labour Supply	1.53
Brooks et al., (2019)	Labour Supply	0.4 – 2.5
Yasmin and Khan (2011)	Labour Demand	0.87
Akhtar and Ali (2007)	Labour Demand	1.07