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MARKET LIQUIDITY PROVISION FOR ON-DEMAND COMPUTING

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ABSTRACT

This paper focuses on a market intermediary's role of liquidity provision to support on-demand computing in a dynamic market trading environment. We outline a framework in which a number of distributed agents sell and buy assets based on their changing utilities over time and a service provider acts as a market maker performing market intervention. We present benchmark models based on socially optimal liquidity provision and a brokerage framework. We then examine the benefits and the dealer's incentives to provide market liquidity.

KEYWORDS: Market microstructure, market dynamics, intermediary, liquidity

INTRODUCTION

On-demand computing is an emerging paradigm for enterprises to manage and use their IT infrastructure, in which computing resources are made available to the user as needed. Radically different from the traditional in-house development and fixed cost infrastructure investments, on-demand computing provides efficiency based on real time acquisition of infrastructure assets. When needed, infrastructure resources such as servers, data storage capacities, and software applications can be acquired from other providers in the network at a spot market price. Conversely, whoever owns those resources can sell them in the market to make a profit if those resources can be more effectively used by others. Pricing on-demand computing in a dynamic market environment is central to this rapidly growing industry.

Emerging economic models for distributed resource management employ computational market-based mechanisms where agents representing available modular services compete to perform tasks to maximize individual utility [1, 4, 7]. Under such framework, resources are generally maintained within the agent's enterprise. Middle agents such as matchmakers or brokers are proposed to address the issue of finding agents in an open environment such as the Internet. At most, those middle agents operate as a central meeting place to help buyers find sellers and vice versa. Current challenge, however, is that the market is not liquid enough to provide real-time match of demand and supply and to aid time-sensitive decision making of distributed agents. An alternative model is to introduce a service provider who acts as a market intermediary and maintains resources availability to meet the fluctuating market demand. However, little is known about the conditions under which the intermediary model is superior to the current brokerage model. We also need to understand the social benefit of liquidity provision on market efficiency and the market maker's economic incentive to provide liquidity. This paper aims to bridge this research gap.

It is well known that market makers in financial markets provide liquidity in order to maintain price continuity and to smooth asset price movement [5]. For example, NYSE specialists use their capital to bridge temporary gaps in supply and demand and help reduce price volatility. Motivated by the success and continuing innovation in financial market operations, [3] propose a bundle-auction market-based approach to optimizing resource allocation in distributed systems. They algorithmically investigated a market dealer's role of market intermediation. They find that the dealer's concentration of resources in her own account can speed up market convergence to an equilibrium allocation. However, in their proposed framework, the dealer employs a static inventory policy where she collects excess resources from market trading and sells them at non-negative market prices. It remains a challenge what the dealer's optimal inventory policy should be, as well as the timing of intertemporal inventory provision. Accordingly, there is a need to further formalize and quantify the dealer's role of market intermediation in a dynamic market trading environment.

Research in the market microstructure literature provides us with an excellent starting point to investigate market efficiency and performance in a dynamic setting [2, 6]. In a search and bargaining model with strategic agents, it is shown in [2] that a monopolistic market maker may provide more intermediation than is socially efficient. In contrast, [6] analyze optimal dynamic liquidity provision during financial disruptions when the market selling pressure is high. It is shown that market makers provide liquidity by absorbing external selling pressure and improve social welfare gains. In our model, we neither impose any assumptions on agents' transaction cost nor initial abnormal market conditions. We assume the market maker is a monopolist who adopts a dynamic pricing strategy and inventory policy to set the market price and influence the order flow in market transaction. Our objective is to characterize various market evolutionary path and possible market outcomes under different market conditions. In the following sections, we specify our market trading environment and market models.

THE MARKET DYNAMICS

In order to model on-demand computing in line with the finance literature, we refer to exchangeable/ tradable computational resources as *assets* and resource users as *agents*. In case that a monopolistic service provider is introduced to maintain, manage, and trade on her own account for the computational resources, we call the service provider as the *dealer*.

We assume both agents and the dealer are risk neutral. Agents have fluctuating demands for assets. To simplify our analysis, we assume agents have two demand levels: high and low. When agents have high demand for resources, we normalize their marginal utility to 1. When agents have low demand for resources, they derive a marginal utility of 0. The dealer does not demand any computational resource so she derives zero marginal utility for holding the asset. Moreover, she incurs an inventory holding cost at rate c per unit time if she carries the asset that she does not need. This suggests that the service provider generally has no incentive to hold asset without proper compensation from the market intervention.

An agent's marginal utility can change over time according to a transition probability. It is reasonable to assume that the intensity of the two transition rates depends on the market price. At an aggregate level, total market demand decreases with an increase in market price. To be

specific, we assume any agent's demand level (and corresponding marginal utility) switches from low to high with rate $\lambda_u(p)$ and switch from high to low with rate $\lambda_d(p)$. We further assume $\lambda_u(p) = e^{-up(t)}$ is a decreasing function of $p(t)$, and $\lambda_d(p) = 1 - e^{-dp(t)}$ is an increasing function of $p(t)$, implying that the transition intensity is consistent with the law of market demand and supply. For instance, when the market overvalues the asset (i.e., p is high), the transition rate from low demand to high demand decreases. This will lessen the burden of demanding the asset which will lead to further increase of the price. Stochastic variations in demand are used to capture a broad range of trading motives such as changes in preferences, beliefs, or requirements for resources. This is a key construct in our model to capture heterogeneity and demand fluctuation in distributed agents, as observed in real markets.

For simplicity, we consider one type of resource (i.e., one asset) in the market. Suppose there is $s \in (0,1)$ shares of asset (i.e., total capacity of available resources in the system) dispersed among agents with population of 1. Each agent holds either 0 or 1 share of an asset. An agent who owns one share is called an owner, and an agent who does not own the asset is called a non-owner. Therefore, there are four possible states for agents:

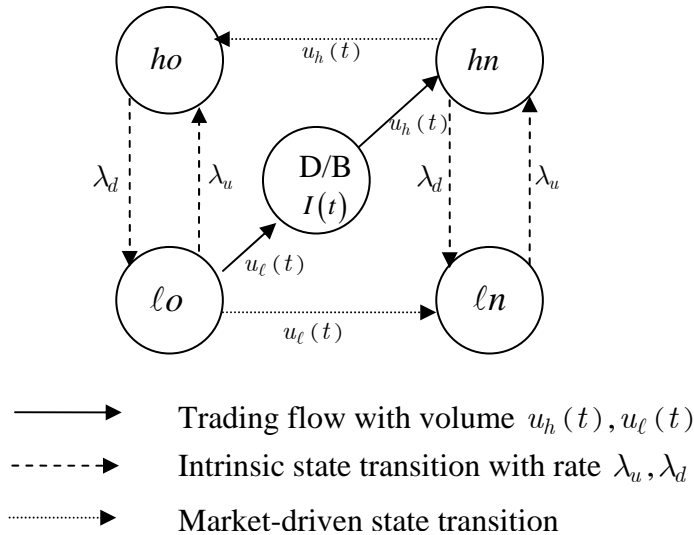
- ho-state*: high marginal utility owner;
- lo-state*: low marginal utility owner;
- hn-state*: high marginal utility non-owner;
- ln-state*: low marginal utility non-owner.

Let ρ_{ij} be the fraction of the population who is in the ij -state. The following identity must hold at any time.

$$\rho_{ho}(t) + \rho_{lo}(t) + \rho_{hn}(t) + \rho_{ln}(t) = 1 \quad (1)$$

The following figure shows the general market model in which a market dealer (D) or a broker (B) intermediates market trading:

FIGURE 1: State Transitions and Market Dynamics



As shown, in this market economy, the ℓo -state agents are sellers and $h n$ -state agents are buyers. Other agents are inactive in market trading. Therefore, at any time instance, the number of market participants varies. This captures the dynamic nature of the market environment. Distributed agents can only trade with the market intermediary (i.e., the dealer or the broker). There are two types of state transition. The trade itself triggers agent state transition. We call it *market-driven* state transition. Agents also transit between “low” and “high” states based on their own intrinsic transition probability λ_u and λ_d . We call it *intrinsic* state transition.

The market intermediary may maintain some inventory $I(t)$ on her own account. If $I(t) \neq 0$ for some t , then we say the market maker is a dealer who performs active market intervention. If $I(t) = 0$ for all t , then the dealer market model is degenerated to the broker market model in which the broker only matches buyers and sellers in the marketplace. At any time, the assets are randomly dispersed among agents and the market intermediary. Namely,

$$\rho_{ho}(t) + \rho_{lo}(t) + I(t) = s \quad (2)$$

Let $u_h(t)$ and $u_\ell(t)$ denote the asset flow rates that the market intermediary transacts with high and low marginal utility agents respectively. The market intermediary's inventory position satisfies

$$\dot{I}_t = u_\ell(t) - u_h(t) \quad (3)$$

The order flow balance equations can be expressed as:

$$\dot{\rho}_{\ell o}(t) = \lambda_d(p) \rho_{ho}(t) - \lambda_u(p) \rho_{\ell o}(t) - u_\ell(t) \quad (4)$$

$$\dot{\rho}_{\ell n}(t) = \lambda_d(p) \rho_{hn}(t) - \lambda_u(p) \rho_{\ell n}(t) + u_\ell(t) \quad (5)$$

$$\dot{\rho}_{ho}(t) = \lambda_u(p) \rho_{\ell o}(t) - \lambda_d(p) \rho_{ho}(t) + u_h(t) \quad (6)$$

$$\dot{\rho}_{hn}(t) = \lambda_u(p) \rho_{\ell n}(t) - \lambda_d(p) \rho_{hn}(t) - u_h(t) \quad (7)$$

For example, equation (4) states that rate of change for the ℓo -state agents consists of three components: the intrinsic transition from ho -state to ℓo -state, the change of ℓo -state to ho -state, and the state transition driven by market trading. The positive sign indicates inflows and the negative sign indicates outflows.

MAKRET LIQUIDITY PROVISION

In this section, we examine the market liquidity provision from two perspectives. Our first objective is to understand the social benefit of liquidity provision. We also propose a brokerage model as another benchmark for comparison. We then study the benefit and the dealer's incentive to provide liquidity in the marketplace. To begin, we state some initial conditions and assumptions of the system.

We assume the initial market price is $0 \leq p_0 < 1$. According to [6], we assume $s < e^{-p_0}$ to ensure that, asymptotically in equilibrium, the number of steady state high marginal utility agents is greater than the number of shares available. Therefore, we assume a problem context of competitive resource allocation. We also assume initially $\rho_{ho}(0) < s$. This implies that the initial allocation of assets in the economy is suboptimal. There is a need to trade in the

marketplace to achieve efficient allocation.

Socially Optimal Liquidity Provision

The socially optimal asset allocation maximizes the total intertemporal utilities of the agents and the dealer. Assume both the dealer and agents discount the future at a constant rate $r > 0$. The dynamic control problem can be expressed as:

$$\begin{aligned} \underset{p(t), I(t)}{Max} \quad & \int_0^{+\infty} e^{-rt} \rho_{ho}(t) dt - \int_0^{+\infty} e^{-rt} c I(t) dt \\ \text{s.t.} \quad & (1) - (7) \end{aligned} \quad (8)$$

The objective maximizes the total social welfare of holding the s shares of asset. From (2) we have two terms. The first term is total utility gains for agents who own the assets (recall that the low demand agents derive zero marginal utility). The second term is the dealer's cost of holding inventory which is defined as the intertemporal utility loss. The constraints are state equations that govern system dynamics. Solution to this optimization problem helps answer the question how much and when liquidity should be provided to maximize social welfare.

The Brokerage Model

Before we proceed to analyze the monopolistic dealer's profit maximization problem, we propose another benchmark scenario in which the dealer does not perform active market intervention. We call this the brokerage model. In this model, the broker charges a fixed percentage b ($0 < b < 1$) of the asset price as the brokerage fee. At any moment t , the broker employs a pricing policy to accept buy or sell orders in order to maximize her discounted total expected net return.

Assume $u_\ell(t) = u_h(t) = \omega(t)$ for all t , then $I(t) = 0$. Revising the conditions in (1)-(7) accordingly we express the new constraints as (1') – (7'). The optimal control problem can be restated as:

$$\begin{aligned} \underset{p(t)}{Max} \quad & \int_0^{+\infty} e^{-rt} b p(t) w(t) dt \\ \text{s.t.} \quad & (1') - (7') \end{aligned} \quad (9)$$

Profit-Maximizing Dealer's Liquidity Provision

Although the dealer incurs a cost at rate c per unit time, she may also make profit by adjusting the market price movement to influence market dynamics and by reselling her inventory to future buyers with a higher market price markup. Hence, the dealer may play an intertemporal role of holding inventory. At any moment t , the dealer employs a pricing policy and inventory strategy to accept buy or sell orders in order to maximize her discounted total expected net profit, defined as the revenue from selling inventory minus the cost of holding inventory. Let $a(t), b(t)$ be the respective ask and bid prices the dealer charges in the market. The optimal control problem can be expressed as:

$$\begin{aligned} \underset{a(t), b(t), I(t)}{Max} \quad & \int_0^{+\infty} e^{-rt} (a(t)u_h(t) - b(t)u_\ell(t) - cI(t)) dt \\ \text{s.t.} \quad & (1) - (7) \end{aligned} \quad (10)$$

The first two terms represent the net profit of the dealer from trading on her own account. The third term is the inventory holding cost.

Solving the optimal control problems (8) - (10) we can gain some fundamental insights about the dealer's pricing and inventory strategies and answer the question how much and when liquidity should be provided from both the social welfare perspective and the dealer's profit maximization perspective. In addition, we are able to compare the proposed dealership framework with the current brokerage model in practice, and further suggest under what conditions which market model makes more sense.

CONCLUDING REMARK

On-demand computing has become a pervasive enterprise computing model in the next frontier of IT deployment. Increasingly complex applications over the Internet consist of distributed agents interacting with each other under a decentralized decision making environment in a real-time manner. Real markets in this type are usually very illiquid, which significantly affects the wide adoption of the emerging IT-enabled on-demand market trading platform. This research contributes to the market efficiency literature by examining market intermediation and liquidity provision in the Internet environment characterized by a group of heterogeneous agents interacting with each other with the aid of a market intermediary. Heterogeneous preferences of agents are modeled as changing marginal utilities that affect their trading decision in a dynamic market environment. Their heterogeneous demands are represented as buy and sell orders according to a stochastic process whose arrival rates depend on the market pricing strategy. We compare two market frameworks: the brokerage market model and the dealership market model. We also study the benefit of liquidity provision from both the social welfare perspective and the dealer's profit maximization perspective. Preliminary results show that complicated tradeoffs exist in market liquidity provision. Please contact the author for a copy of the research paper.

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