Commodity Trade Finance Platform using Distributed Ledger Technology

Token Economics in a Closed Ecosystem using Agent Based Modeling

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Distributed Ledger Technology (DLT) creates a decentralized system for trust and transaction validation using executable smart contracts to update information across a distributed database. This type of ecosystem can be applied to Commodity Trade Finance to alleviate critical issues of information asymmetry and the cost of transacting which are the leading causes of the Trade Finance Gap (ie. the lack of supply of capital to meet total trade finance demand).

The possibility of scaling up such ecosystems with a number of Institutional Investors and micro small medium enterprises (MSME) would be advantageous, however it brings up its own set of challenges including the stability of the system design.

Agent-based modeling (ABM) is a powerful method to assess the financial ecosystem dynamics. DLT ecosystems model well under ABM, as the agents present a clearly defined taxonomy.

In this study, we use ABM to assess the Aquifer Institute Platform - a DLT-based Commodity Trade Finance system, in which a growing number of participating parties is closely related to the circulation of utility tokens and transaction flows. We study the system dynamics of the platform and propose an appropriate setup for different transaction loads.

I. INTRODUCTION

Modern Commodity Trade Finance is built on a system of letter of credits (L/C) which allow seller and buyer to guarantee execution of operations by having a bank take the counterparty risk (availability of funds for term transactions) on to its balance sheet.

Over the years, a dramatically growing Trade Finance Gap has plagued international trade. According to the Asian Development Bank this unmet demand was around \$1.5 trillion in its 2017 survey [7]. Due to increased regulatory requirements, banks have either closed their commodity finance businesses or focused on high volume borrowers leaving small to medium firms aside, thus increasing the funding deficiency in the market.

Many borrows are also seeing their applications for trade finance rejected due to a lack of transparent financial information or track record (leading to unacceptably high and/or possibly mispriced credit risk).

While banks reduce activity in commodity trade fi-

nance, this opportunity is attracting institutional investors who benefit from having broad mandates to allocate capital over a range of trade finance transactions. These trade finance funds recognize the underlying value of the commodity collateral which allows them to manage the commodity risks more effectively. Scarcity of credit has also driven the yields demanded by investors higher, in turn increasing the attractiveness of the investment.

DLT brings with it a set of definitive solutions to Commodity Trade Finance; Firstly, its decentralized nature improves the balance of power between parties making transactions more equitable; The ability to validate transactions automatically and execute when predefined conditions are met reduces the labor requirements and need for an intermediary thereby abolishing the L/C paper cycle, which has added significant operational costs and transaction time to the transaction workflow; Finally, a decentralized ledger offers a trust network that increases transparency and helps to reduce information asymmetry in trade finance [7].

With increased operational efficiency and reduced transaction time, a DLT-based Trade Finance Platform ultimately allows high scalability, by allowing a large number of MSME and trading houses to attract financing by multiple institutional investors outside of the traditional Trade Finance industry. This in turn requires careful assessment of the basic transactions to ensure that the ecosystem is functioning well at scale.

The Aquifer Institute offers a DLT-based Commodity Trade Finance Platform which reduces the cost of financing, speeds up transactions and lower the risks of fraud. Here the KYC is taken over by the Platform and Trading Houses, allowing Financiers to focus on essential properties of a particular Request for Finance (RFF). The Platform uses internal utility tokens (Aquifer Institute Coin - AIC) to enable flow between financiers, trading houses, buyers and sellers both on and off the DLT.

As transactions on the Aquifer Institute Platform rely heavily on the circulation of AIC tokens, it is crucial to ensure its liquidity as the number of participants in the platform and corresponding transactions scales up.

II. ABM FOR AQUIFER ECOSYSTEM

To measure the viability and resilience of the Aquifer Institute Platform at scale, we built a simulation model using an Agent-Based Model that reproduces the essential features of the ecosystem. Such an analysis allows us to investigate transactions and capital flow within the

future ecosystem as well as their dynamics and complexity as the numbers of requests for financing (RFF) and financiers grow.

It is worth noting that the system at hand had not been considered for ABM analysis previously, but its building blocks are reminiscent of those analysed in context of order books dynamics [10, 11, 18], trading [5, 15, 22] and auctions [19, 21, 23]. We refer interested readers to Appendix A for more details.

A. Model Architecture

FIG. 1. The architecture of the ABM for Aquifer Institute Trading Finance platform; The platform acts as a container for all the other modules. Trading Houses generate a stream of waiting Requests For Financing (RFFs) which could receive financing from Financiers via Auction. Over its lifetime an RFF contract may become active and then closed, be rejected or expired.

The modular structure of the platform is reflected in an ABM model architecture as shown in Figure 1. The first module is the **Platform**. It acts as a container for other objects in the Ecosystem; it is responsible for running the interactions between various components, and facilitates the token circulation. The Platform hosts **Trading Houses**, which create a number of RFFs on a daily basis. All prospective onboarded Trading Houses are modeled as one as it doesn't functionally affect the system. Once RFFs are generated, they are passed to the Platform (after paying a fee in AIC tokens), which warehouses them as Waiting (effectively, waiting for financing), Active (financing has been secured, with the contract currently being processed), Closed (the duration of the contract is ended), Expired (the RFF did not secure financing over the limited lifetime) or Rejected (the RFF did not acquire financing because it was lacking Platform tokens). The latter case is undesirable and is used to mark functional boundaries of our model.

The **Financiers** represent another type of agent of the Platform ecosystem. They join with an initial capital, initially drawn from a selected distribution. Financiers bid for the right to finance waiting RFFs where the asso-

ciated interest rate is determined by the outcome of the auction process. The **Auction** module can be run multiple times per day to utilize maximum amount of RFFs and available capital. A Reverse Vickrey auction is used as is induces truthful bidding as a dominant strategy.

B. Discrete Time Dynamics

The Aquifer Institute Platform has clearly defined discrete time steps (e.g. days) which map directly to a corresponding sequence of steps in ABM. Every day a set of steps is performed as described below.

Step 1. The Trading House generates a daily set of RFFs. After paying a fixed fee (in AIC tokens) the RFF is added to a Waiting list on the platform. In reality, the fee is introduced to cover the expense of deploying a corresponding contract on the public Ethereum blockchain, or a different chain.

Step 2. Financiers evaluate Waiting RFFs according to a given strategy.

Step 3. Each Financier selects the RFFs that it wishes to participate in, such that it has the sufficient capital to meet the financing requirements. Financiers pay a daily entry fee in AIC tokens to participate in the RFF Auctions.

Step 4. A Reverse Vickrey Auction is applied for each Waiting RFF, where bids represent interest rates proposed by Financiers. The auction is valid if more than two Financiers have participated.

Step 5. Financiers' funds are "locked" on their account for the total amount of winning RFFs. Simultaneously, the Trading House is required to "purchase" and lock enough AIC tokens to cover interest payment for the RFF over the entire period of financing. RFFs are then moved to the Active RFFs list. If the Platform faces a lack of tokens to "sell" to the Trading House to cover their interest payment, then the RFF is moved to Rejected RFF list (undesirable).

Step 6. RFFs which stay in the Waiting list longer than "RFF lifetime" are moved to an "Expired RFFs" list.

Step 7. On completion of the period of financing, the funds are returned to the Financier together with the interest payment in tokens (with platform commission extracted). The Financier swaps tokens to fiat currency. Interest is capitalized, i.e. financiers add received interest amount to capital for financing new RFFs. Finally, the RFF is moved to a "Closed RFFs" list.

C. Capital Flow and Token Circulation

The steps above presume sufficient flow of capital and token circulation. As AIC tokens are locked for the interest payback and transaction fees, there should be enough supply of tokens to run each transaction. Below we describe in detail the flow of tokens and capital circulation

FIG. 2. Capital flow and token circulation in the Platform. Green dashed lines show AIC token circulation and blue solid lines represent flow in Fiat currency. The inflow of Capital in the Platforms is via the Trading Houses which attract external funds to cover the interest rates of the funds.

in the system.

Figure 2 depicts the high-level scheme of capital flows (blue lines) and token circulation (green dashed lines) between the main agents: Platform, Trading House and Financiers. Here we assume that the initial funds of the Platform and Financiers are fixed while the Trading House will acquire external funds to pay interest to Financiers, leading to an inflow of the capital in the Platform ecosystem, i.e. increase of the Financiers' funds. The fiat currency (capital) circulates between Financiers and the Trading House as a loan with the Platform not involved in the circulation of fiat between parties. The other types of capital flow are related to the purchase and sale of AIC tokens and are done by Financier or Trading House on one side and Platform on the other. Tokens are used to make payment of fees to submit or to place bids on RFFs, and to lock and pay interest or commissions. Hence, enough tokens in the system is vital for its efficient performance.

The considered model assumes instant exchange of tokens, so that Financiers exchange received tokens to fiat currency immediately upon receiving. In the same manner, tokens are purchased from the platform only as they are needed. The reality may show some discrepancies with this assumption, but it is natural to assume that there is no need to keep an extended amount of tokens as it would tie up capital with limited utility.

D. Auction Design

At the beginning of each day a number of Reverse Vickrey auctions are initialized for each RFF from the Waiting list. Financiers bid by submitting interest rates, with the winner (if any) being the lowest submitted bid. The winning submitter will lend capital at the level of the second lowest bid. This design of the auction induces truthful bidding as a dominant bidding strategy and reduces speculative and collusive behavior.

FIG. 3. A schematic picture of the Reverse Vickrey Auction. Financiers submit bids for waiting RFFs (RFF1 - RFF4), based on their limited funds. This in turn means some RFF Auctions have multiple bids, while others have single bids or none leading to a Rejected RFF. The winning bidder will be rewarded by transacting at the second lowest bid rate in the auction.

A Financier may participate in an auction if it has enough capital to cover the request and has paid an entry fee in AIC tokens. Participation in a number of auctions is allowed as long as there is enough capital to cover all the requests (auctions). The fee is expected to be nominal such that it will not change the strategic behavior of the Financiers. The auction is considered to be successful if it has attracted at least two financier bids. In case of a single bidder, the auction is considered not successful, and either another round of auction is held on the same day or the RFF is delayed until the second day.

Using the daily utilization of free capital as a metric can raise some concerns. The upper threshold in a single auction round is 50% – to run the auction one needs at least two bidders (financiers) who have enough capital to cover the request. In simulations we observe this metric to be up to 30%. This fraction may be increased by conducting multiple auction rounds during the same day, i.e. all unsatisfied RFFs may be passed to a second round. On the other hand the utilization of total capital is significantly higher than that of the utilization of free capital. Once winning an RFF session, the corresponding capital volume is utilized for the entire duration of the contract. This can lead to approximately 90% of the total Financier capital being in use on a daily basis if there are enough tokens to run all the transactions. One of the purposes of the simulations conducted here is to study the system dynamics of the platform. See Result section for more details on this.

E. Financiers' Strategy

The valuation of the RFF is a complex process which involves analysis of the properties of a particular trade against the required rate of return (yield/interest rate) for the Financier. Since the underlying process is specific for each Financier and the empirical data is scarce, this de-

tailed modeling is outside the scope of the present study. We use a Reverse Vickrey Auction with a Cutoff strategy [19]. Here the Cutoff represents a limited amount of information available for the Bidder in the Auction [13], i.e. an idea of the latest median interest rate for some Commodity type.

We assume that Financiers are ex-ante symmetric, their valuations p_i are drawn from the same distribution. In the first approximation the Financiers' valuation strategy may be an independent and identically distributed (IID) sample from one of the long-tail distributions. For this we use a Beta distribution, which is a skewed long-tail distribution defined on the interval $[0, P]$. The value P may represent the upper bound of financiers' bidding price or cost of capital outside of the Platform – we set $P = 0.5$ in our simulations. The probability density and Cumulative distribution functions are given by

$$f_{\text{beta}}(x, \alpha, \beta) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1},$$

$$F_{\text{beta}}(x, \alpha, \beta) = \frac{B(x; \alpha, \beta)}{B(\alpha, \beta)}$$

where B being the beta function and α, β the tuning parameters controlling the shape of the distribution. The Beta distribution can appear as a stationary limit in bounded interest rate models governed by a Markov stochastic process [6]. We choose $\alpha = 2$ and $\beta = 20$ such that the mean value of distribution is located approximately at a 9% interest rate.

Once the RFF gets its valuation, the strategy for the bidding depends on participation cost $c \in [0, P]$ and a cutoff p^* which is common for all the financiers and is set as an external parameter in the simulations. For each Financier the resulting bid strategy is

$$b_i = \begin{cases} \text{No} & \text{if } p_i > p_i^* \\ p_i & \text{if } p_i \leq p_i^* \end{cases}.$$

In the Appendix C we show that for $p^* = P$ and $c \rightarrow 0$ (participation cost is negligible) such auction design results in a unique equilibrium and all participants tend to bid, given they have enough capital. The introduction of the platform commission barely changes the bidding strategy and participants only lift their price to cover the commission.

III. DETERMINISTIC MODEL

In this section, we consider an idealistic *deterministic* model to obtain some insights of the platform's operations. In this deterministic model, no randomness presents. We first specify the model parameters.

1. Trading houses

- (a) The number of RFFs generated per day is N .
- (b) Each RFF requests R units of capital.

- (c) Each RFF's duration is D days.

2. Financiers

- (a) The number of financiers is M .
- (b) Each financier has C units of capital.
- (c) All financiers have the same average interest rate valuation $v < 1$ on each RFF.

3. Platform

- (a) Perfect match between RFF and capital, without single-bidder-no-winner issue. So whenever there are waiting RFFs and idle capital, the auction matches them. Hence, the number of auction rounds per day Q is immaterial here.
- (b) The platform holds *sufficient* number of tokens, i.e., $T \rightarrow \infty$ to facilitate all related activities and it allows *immediate* exchange between AIC and fiat currency.

Specifically, we want to understand the following questions through studying this deterministic model.

1. When facing a certain volume of RFFs per day, what is the amount of total capital required to finance these RFFs? Or equivalently, for a given amount of total capital, what is the right volume of RFFs per day to feed the platform?
2. How many tokens are required to support the financing activity of certain volume of RFFs?

The *total* capital held by financiers is $M \cdot C$ and the amount of capital required to fulfill *all* RFFs is $N \cdot R \cdot D$. If the financiers' total capital is not enough to fulfill all RFFs, i.e., $M \cdot C \leq N \cdot R \cdot D$, the utilization of financiers' capital is 100%, and the fraction of RFFs fulfilled is $\frac{M \cdot C}{N \cdot R \cdot D}$. If the financiers have enough capital to fulfill all RFFs, i.e., $M \cdot C \geq N \cdot R \cdot D$, the utilization of financiers' capital is $\frac{N \cdot R \cdot D}{M \cdot C}$, and the fraction of RFFs fulfilled is 100%. Clearly, the best scenario is that all RFFs are fulfilled and financiers' capital is utilized at 100%; i.e.,

$$M \cdot C = N \cdot R \cdot D. \quad (1)$$

On any day, the total amount of interest payment locked up on the platform, in the form of tokens, is

$$T = N \cdot R \cdot D \cdot (v \cdot D / 365), \quad (2)$$

which is an indicator of the amount of tokens required to sustain the platform.

Of course, the above insights are only true in the idealistic deterministic setting without any randomness. In reality, the presence of randomness will have an effect on, (i) the RFF fill rate, (ii) the capital utilization, and (iii) the total amount of locked up interest payment. We next discuss how the relaxations of these idealistic assumptions will affect these three measures.

The number of auction rounds Q per day determines the matching probability between capital and RFFs. Intuitively, the matching probability increases with Q . The more tokens T the platform issues, the lower the chance a trading house cannot find/buy tokens to pay to the financiers. Of course, we may not need infinite tokens to support the platform activity, but only an proper amount. If the exchange between tokens and fiat is not immediate, then the total amount of tokens should increase.

If either the number of RFFs per day N , or RFF's requested capital R , or RFF's duration D becomes a random variable instead of a constant value, the RFF fill rate and the capital utilization will drop from 100%. However, the magnitude of the fall is still not clear to us. Moreover, the amount of interest payment locked up in the form of tokens may increase or decrease. Hence, we need the following simulation model to investigate the effect of randomness.

IV. SIMULATION MODEL

In this section, we relax the assumptions in the deterministic model and incorporate randomness using a simulation model. We want to understand the effect of using (1) and (2) to guide the platform's token circulation. Furthermore, we want to answer the question: how many auction rounds per day should be held. Thus, in the simulation, we focus on the steady state analysis and do not return interest payment back to financiers at the end of the RFF duration, so that the total capital amount is constant during these 3600 days in the simulation. The settings of the simulation model are listed below.

1. Trading houses

- (a) The number of RFFs generated per day is *Uniformly* distributed with mean N on $\{N - 5, N - 4, \dots, N + 4, N + 5\}$.
- (b) The capital request of each RFF *Uniformly* distributed on $[0.5, 1.5]$ with mean $R = 1$.
- (c) Each RFF's duration is *Uniformly* distributed on $[30, 90]$ with mean $D = 60$ days.

2. Financiers

- (a) The number of financiers is $M = 5$.
- (b) Each financier has C units of capital.
- (c) Each financier's valuation of each RFF is *Beta* distributed on $[0.05, 0.5]$ with mean $v = 9\%$.

3. Platform

- (a) The number of auction rounds per day is Q . The single-bidder-no-winner issue may occur.
- (b) Total number of tokens (measured in capital) is T . The platform allows *immediate* exchange between tokens and fiat currency.

A. Auction Rounds

More auction rounds per day Q reduces the probability of single-bidder-no-winner case, and improves the successful matching rate between RFF and capital, given all other parameters are held the same. Here, we set the total number of tokens as five times of the value prescribed by the idealistic model in (2), i.e., $T = 5 \cdot N \cdot R \cdot D \cdot (v \cdot D / 365)$, so that there are surely sufficient tokens to support the daily activities on the platform, such as locked up interest payment, entry fee for auctions, RFF listing fee, etc. Furthermore, we set the total capital $M \cdot C$ to be the same as the expected capital required to fulfill all RFFs $N \cdot R \cdot D$.

Figure 4 illustrates the RFF fill rate as a function of the total capital under different auction rounds per day $Q \in \{1, \dots, 5\}$. First, we see that the RFF fill rate in the simulation is less than 100% – the perfect fill rate in the deterministic model. This is due to the randomness introduced in the simulation model. However, the gap is not big: in almost all experiments, the RFF fill rates are above 95%.

Second, we observe that increasing the auction rounds per day Q improves the RFF fill rate. When only one round of auction is held per day, i.e., $Q = 1$, the RFF fill rate is below 96%. When Q is increased to 5, the RFF fill rate is above 98%. The main improvement is when Q increases from one to three. When Q increases to above three, the improvement is not that obvious.

FIG. 4. RFF fill rate as function of the total capital for $\{1, 2, 3, 4, 5\}$ auction rounds per day.

Similar phenomenon can be observed in Figure 5, where the capital utilization is plotted as a function of the total capital Ω under different auction rounds per day $Q \in \{1, \dots, 5\}$.

Hence, we conclude that three auction rounds per day, i.e., $Q = 3$, will be sufficient to reach a reasonable match between RFFs and capital. We then use $Q = 3$ in the following other simulation experiments.

FIG. 5. Capital utilization as function of the total capital for $\{1, 2, 3, 4, 5\}$ auction rounds per day.

B. Number of Tokens

The total number of tokens T defines the capacity of the platform, where tokens are used to pay the RFF listing fee, entry fee to the auction, and perhaps mainly locked up as interest payment from trading houses to financiers. In this section, we focus on the total number of tokens needed to satisfy the function of locked up interest payment and assume negligible fees.

Figure 6 shows the RFF fill rate as a function of the total capital under different numbers of tokens T . First, we see that the token volume proposed in (2), i.e., $T = N \cdot R \cdot D \cdot (v \cdot D/365)$, is not sufficient to support the platform function. The RFF fill rate is quite volatile in the range of $[80\%, 85\%]$ as a function of the total capital. Second, if we increase the number of tokens to $T = 3 \cdot N \cdot R \cdot D \cdot (v \cdot D/365)$, the RFF fill rate increases significantly to over 95%. However, further increasing the total number of tokens does not improve the RFF fill rate much.

FIG. 6. RFF fill rate as function of the total capital for $F \in \{1, 2, 3, 4, 5\}$ times $N \cdot R \cdot D \cdot (v \cdot D/365)$ tokens.

We have the similar observation from Figure 7, where the capital utilization is a function of the total capital

under different numbers of tokens. Hence, we choose $T = 3 \cdot N \cdot R \cdot D \cdot (v \cdot D/365)$ to be an optimal amount of tokens for the platform operations.

FIG. 7. Capital utilization as function of the total capital for $F \in \{1, 2, 3, 4, 5\}$ times $N \cdot R \cdot D \cdot (v \cdot D/365)$ tokens.

Of course, there are other factors affecting the total number of tokens needed by the platform. For example, we assume immediate exchange between tokens and fiat currency, but in reality the exchange may not be immediate, or platform participants may delay their exchange from tokens to fiat for some reasons. These will all increase the required number of tokens needed to support the platform operations.

C. Ratio of RFF and Total Capital

In Sections IV A and IV B, we set the total capital $M \cdot C = N \cdot R \cdot D$, which is the relationship obtained from the deterministic model in Section III. In this section, we vary this ratio to investigate the proper relationship between the amount of capital required by RFFs $N \cdot R \cdot D$ and the financiers' total capital $M \cdot C$.

In Figures 8 and 9, we plot the RFF fill rate and the capital utilization as functions of the total required capital for different total capital. First, we see that when the total capital is less than the required capital by RFFs, e.g., $M \cdot C = \frac{9}{10} N \cdot R \cdot D$, the RFF fill rate is below 90%, while the capital utilization is high around 97.5%. Next, if the total capital is more than the required capital by RFFs, e.g., $M \cdot C = \frac{10}{9} N \cdot R \cdot D$, all RFFs are fulfilled, while the capital utilization is low at 90%. Lastly, when $M \cdot C = N \cdot R \cdot D$, both the RFF fill rate and the capital utilization are above 95%.

Of course, the ratio between the amount of capital required by RFFs $N \cdot R \cdot D$ and the financiers' total capital $M \cdot C$ shall be determined by the platform's long-term strategy. Nevertheless, the relationship $M \cdot C = N \cdot R \cdot D$ appears to bring a nice balance between the RFF fill rate and the capital utilization.

FIG. 8. RFF fill rate as function of the total capital for total capital of $\Omega \in \{9/10, 1, 10/9\}$ times $N \cdot R \cdot D$.

FIG. 9. Capital utilization as function of the total capital for total capital of $\Omega \in \{9/10, 1, 10/9\}$ times $N \cdot R \cdot D$.

D. Other Factors

There are other factors that may affect the required amount of tokens for platform operations $T = 3 \cdot N \cdot R \cdot D \cdot (v \cdot D/365)$ and the required amount of capital to cover a certain amount of RFF requests $N \cdot R \cdot D$. We next discuss these factors.

Given other parameters are fixed, the higher the interest rate v , the more tokens are required to sustain the platform operations. One may expect close to the (reverse) linear dependency, since the amount of locked tokens that are reserved for interest payments is proportional to interest rate assuming no higher order correlations (e.g., RFF volume and interest rate). Some discrepancies may be related to usage of tokens for various platform fees.

If the RFF duration D becomes longer, the platform needs more tokens to support the same volume of RFFs, and a linear increase can be expected. Note that RFF duration has a linear correlation with the interest payment given a fixed interest rate. These two factors result in a quadratic dependence between the RFF duration and the

number of tokens required to run all Platform functions smoothly.

Interestingly, the number of financiers, given the same total financier capital, may also affect the amount of tokens required to support platform operations. More financiers on the platform (i.e., M increases) will reduce the RFFs' interest payment to financiers. Imagine an infinite number of financiers have a common valuation distribution on the RFF interest rate with a support on $[0.05, 0.5]$, and they bid on a specific RFF. The financier who bids 0.05 will win the auction, and she will pay the second lowest bid, which should be very close to 0.05 due to the infinite number of financiers. The conclusion is that we should not have too many financiers on the platform; otherwise, none of them will be able to generate sufficient return. The platform may consider increasing the capital amount per financier to increase the total capital on the platform, instead of increasing the total number of financiers.

V. CONCLUSIONS

DLT-based solutions offer a higher efficiency of Commodity Trade Finance by leveraging the decentralized nature of Blockchain for trust in transaction validation and smart contracts through cost and time optimization of transactions.

The essential link in such solutions is the utility token circulation which incorporates platform costs, transaction fees and interest rate payments. This in turn leads to complex interactions between participants in the platform, possible accumulation of tokens in some accounts and resulting liquidity squeezes.

Aquifer Institute provides a Trade Finance platform which utilizes the above advantages of DLT and moves KYC checks to Platform and Trading Houses which simplifies processes for Financiers and allows for a natural scaling in their number. The Platform uses AIC tokens to run the transactions so it is of central importance to ensure efficient circulation through scaling.

In this paper, we study the Aquifer Institute Platform and generate insights into its operations. We want to understand that to handle a certain volume of RFFs, what is the total capital needed on the financiers' side, and how many tokens are required to support the operations. From a deterministic model, we have the understanding that (i) the ratio between the amount of capital required by RFFs and the financiers' total capital should follow (1); and (ii) the total amount of tokens needed is given in (2).

Furthermore, we take randomness into account using a simulation model to examine (1) and (2). We discover that (i) the ratio proposed in (1) brings a nice balance between the RFF fill rate and the capital utilization; and (ii) the total amount of tokens on the platform can be set as $T = 3 \cdot N \cdot R \cdot D \cdot (v \cdot D/365)$ to ensure smooth operations.

Moreover, we identify other factors that may affect the required amount of tokens for platform operations and the required amount of capital to cover certain amount of RFF requests.

In this study, the Platform recreated in an ABM enables the exploration of the parameters which are either not accessible or dangerous in a real system. With the availability of real-world performance data, such a model can be fine-tuned and effectively used as a risk-assessment and predictive tool to evaluate Platform efficiency and dynamics.

Appendix A: Detailed overview of ABM literature

One of the key purposes of using Agent-Based Modeling is to simulate real system behavior, keeping only essential degrees of freedom. This corresponds to the zero-intelligence or basic models. Examples of such models are the order book models [10, 11, 18], where the orders are submitted in a random way on the grid of prices (i.e. there is a discrete range of possible prices). While they are not directly linked to commodity markets or a similar ecosystem to AI, the approach may be useful for our modeling. Simulations of market dynamics are usually done by discretizing the process in time steps during which a fixed set of actions could take place. For the order book dynamics this is similar to physical simulations of particles (orders) on the grid (discrete values of prices) [1]. Such an analogy is often useful in terms of understanding scaling laws as the system is growing and its universality class, which is a well-studied topic in statistical physics. Having a zero-model and discretized simulation procedure means the complexity of the model could be gradually increased to reproduce various empirical behavior. This could include more realistic approaches to bid placements. In the order book models, this allowed the ability to reproduce a realistic non-Gaussian heavy tailed distributions for returns [16] and correct Hurst exponent of the price time series [3].

The model may be further complicated by incorporating more realistic assumptions. The first realistic assumption would be to include herding behavior (Collusion) between participants. This was elegantly done in [5] where there is a diffusion of information between agents at each time step. At each time step agents are re-linked with some probability and form the network. With such a simple assumption, authors were able to reproduce a distribution of price variations that were very close to empirical data. Second, another important assumption would be on behavioral characteristics for different agents like Financier valuations and bidding strategies. In [15] and [22] two types of trades were introduced: fundamentalists whose trade volume is linked to price deviations from some fundamental value and chartists who follow the trend on the market.

Once the model is settled and the simulations are conducted, one may inspect a phase diagram of the system, see e.g. [2]. This analysis includes scanning of the sys-

tem behavior under varying parameter space. Different phases will be linked to entirely different behavior under the given metric.

Appendix B: Auction strategies

Auctions are used to allocate resources among competitive buyers and to estimate a real price of the resource. There are three types of agents: sellers, buyers and auction designer. The purpose of a seller is to maximize revenue while the buyer would like to maximize their payoff or net utility. The auction designer is interested in truthful bidding, and an efficient and fair outcome.

Among different types of auctions we consider sealed-bid auctions, where all information is closed until the auction results are shown to the 'public'. The valuation environment is one of the ingredients that affect the outcome. Independent private value and common value are two sides of the edge. Under independent private value each bidder knows its own valuation and is not concerned with valuations of the other agents, see e.g. [8]. Under the common value environment, which is typical for resale, the resource value is identical for all bidders, which is not necessarily known to the agents.

The auctions may be classified according to the number of items to be sold: single or multiple items. It is known that under the private value environment that a single item may be truthfully sold with a Vickrey auction design [21] assuming risk-neutral bidders. It allocates the item to the bidder who proposed the highest price for the second-price value. There are a variety of Vickrey auction generalizations towards a multi-item case: Generalized Second Price (GSP) [9, 20] and Vickrey-Clarke-Groves (VCG) [4, 12, 21]. Although the latter induces truthful bidding, its mechanism is quite difficult to explain to the wide audience and thus it is not used often in practice. AI approaches this problem by considering each RFF session as an independent single-item auction with Vickrey design rules.

Within the Platform, Financiers submit an interest rate as their bid, with the winner being the bidder with the lowest rate and will receive the interest calculated based on the second-lowest interest rate. Such a design is called a reverse auction. The existence of the entry fee may affect the auction outcome. This is the case, however, only when this fee is above some cutoff threshold. Under the private value environment once a bidder has decided to participate the true valuation is a dominant strategy, see e.g. [14, 17, 19, 23].

Appendix C: Equilibrium in a Reverse Vickrey auction

Lemma 1 *Let $p_i^* \in [0, 1]$ be the cutoff used by financier i where $p_1^* \leq p_2^* \leq \dots \leq p_n^*$. Define $p_0^* = 0$ and $p_{n+1}^* = P$. Cutoff strategies given by $\{p_i^*\}_{i=1}^n$ constitute a Bayesian-*

Nash equilibrium iff for financier i

$$\sum_{j=i}^n \left\{ \left[\prod_{\substack{k=1 \\ k \neq i}}^j \bar{F}(p_k^*) \right] \int_{p_j^*}^{p_{j+1}^*} \bar{F}(p)^{n-j} dp \right\} - c \leq 0$$

satisfied with equality.

Proof. Arbitrary financier i with reservation price $p_i = p_i^*$ (i.e., reservation price is cutoff value) will participate.

For her to win this reverse auction, all other *participating* financiers must have reservation prices greater than p_i^* . This means that (i) financiers whose cutoffs are greater than p_i^* have reservation prices greater than p_i^* so they may participate in the reverse auction but will not win. (ii) Financiers with cutoffs lower than p_i^* have reservation prices greater than their respective cutoffs so they will not participate in the reverse auction, otherwise one of them will win the reverse auction.

Financier i 's payoff when her reservation price is at the cutoff value p_i^* and she participates, is:

$$\begin{aligned} & \prod_{k=1}^{i-1} \bar{F}(p_k^*) \left\{ (p_{n+1}^* - p_i^*) \prod_{k=i+1}^n \bar{F}(p_k^*) + \left[\prod_{k=i+1}^{n-1} \bar{F}(p_k^*) \right] \int_{p_{n-1}^*}^{p_n^*} (p - p_i^*) dF(p) \right. \\ & + \cdots + \left[\prod_{k=i+1}^{n-j} \bar{F}(p_k^*) \right] \int_{p_{n-j}^*}^{p_{n-j+1}^*} (p - p_i^*) dF(p)^j + \cdots + \left. \int_{p_i^*}^{p_{i+1}^*} (p - p_i^*) dF(p)^{n-i} \right\} - c \\ & = \left[(p_{n+1}^* - p_i^*) \prod_{\substack{k=1 \\ k \neq i}}^n \bar{F}(p_k^*) + \int_{p_{n-1}^*}^{p_n^*} (p_i^* - p) d\bar{F}(p) \prod_{\substack{k=1 \\ k \neq i}}^{n-1} \bar{F}(p_k^*) \right. \\ & + \cdots + \left. \int_{p_{n-j}^*}^{p_{n-j+1}^*} (p_i^* - p) d\bar{F}(p)^j \prod_{\substack{k=1 \\ k \neq i}}^{n-j} \bar{F}(p_k^*) + \cdots + \int_{p_i^*}^{p_{i+1}^*} (p_i^* - p) d\bar{F}(p)^{n-i} \prod_{\substack{k=1 \\ k \neq i}}^i \bar{F}(p_k^*) \right] - c \\ & = \left\{ (p_{n+1}^* - p_i^*) \prod_{\substack{k=1 \\ k \neq i}}^n \bar{F}(p_k^*) + \left([\bar{F}(p)(p_i^* - p)]_{p_{n-1}^*}^{p_n^*} + \int_{p_{n-1}^*}^{p_n^*} \bar{F}(p) dp \right) \prod_{\substack{k=1 \\ k \neq i}}^{n-1} \bar{F}(p_k^*) \right. \\ & + \cdots + \left([\bar{F}(p)^j(p_i^* - p)]_{p_{n-j}^*}^{p_{n-j+1}^*} + \int_{p_{n-j}^*}^{p_{n-j+1}^*} \bar{F}(p)^j dp \right) \prod_{\substack{k=1 \\ k \neq i}}^{n-j} \bar{F}(p_k^*) \\ & + \cdots + \left. \left([\bar{F}(p)^{n-i}(p_i^* - p)]_{p_i^*}^{p_{i+1}^*} + \int_{p_i^*}^{p_{i+1}^*} \bar{F}(p)^{n-i} dp \right) \prod_{\substack{k=1 \\ k \neq i}}^i \bar{F}(p_k^*) \right\} - c \\ & = \left\{ (p_{n+1}^* - p_i^*) \prod_{\substack{k=1 \\ k \neq i}}^n \bar{F}(p_k^*) + [\bar{F}(p)(p_i^* - p)]_{p_{n-1}^*}^{p_n^*} \prod_{\substack{k=1 \\ k \neq i}}^{n-1} \bar{F}(p_k^*) + \cdots + [\bar{F}(p)^j(p_i^* - p)]_{p_{n-j}^*}^{p_{n-j+1}^*} \prod_{\substack{k=1 \\ k \neq i}}^{n-j} \bar{F}(p_k^*) \right. \\ & + \cdots + \left. [\bar{F}(p)^{n-i}(p_i^* - p)]_{p_i^*}^{p_{i+1}^*} \prod_{\substack{k=1 \\ k \neq i}}^i \bar{F}(p_k^*) \right\} + \sum_{j=i}^{n-1} \int_{p_j^*}^{p_{j+1}^*} \bar{F}(p)^{n-j} dp \left[\prod_{\substack{k=1 \\ k \neq i}}^j \bar{F}(p_k^*) \right] - c \\ & = (p_{n+1}^* - p_n^*) \left[\prod_{\substack{k=1 \\ k \neq i}}^n \bar{F}(p_k^*) \right] + \sum_{j=i}^{n-1} \int_{p_j^*}^{p_{j+1}^*} \bar{F}(p)^{n-j} dp \left[\prod_{\substack{k=1 \\ k \neq i}}^j \bar{F}(p_k^*) \right] - c \\ & = \sum_{j=i}^n \left\{ \left[\prod_{\substack{k=1 \\ k \neq i}}^j \bar{F}(p_k^*) \right] \int_{p_j^*}^{p_{j+1}^*} \bar{F}(p)^{n-j} dp \right\} - c \leq 0 \end{aligned} \tag{C1}$$

■

Proposition 2 *There exists a unique equilibrium with a common valuation cutoff $p_i^* = p^s \in (c, P)$ where*

$$\bar{F}(p^s)^{n-1} (P - p^s) - c = 0 \quad (C2)$$

as long as the distribution F and the participation cost c satisfy the relationship $\bar{F}(c)^{n-1} (P - c) - c > 0$.

Proof. If we impose symmetry, i.e., $p_i^* = p^s \forall i$, (1) be-

comes

$$\begin{aligned} \left[\prod_{\substack{k=1 \\ k \neq i}}^n \bar{F}(p^s) \right] \int_{p^s}^{p_{n+1}^*} \bar{F}(p)^{n-n} dp - c &\leq 0 \\ \bar{F}(p^s)^{n-1} (p_{n+1}^* - p^s) - c &\leq 0 \\ \bar{F}(p^s)^{n-1} (P - p^s) - c &\leq 0 \end{aligned}$$

We have $\bar{F}(p^s)^{n-1} (P - p^s)$ is continuous and *strictly decreasing*. Next we want to show cutoff $p^s \in (c, P)$.

$$\begin{aligned} \text{If } p^s = P, \bar{F}(p^s)^{n-1} (P - p^s) - c &= \bar{F}(1)^{n-1} (P - P) - c = -c < 0 \\ \text{If } p^s = c, \bar{F}(p^s)^{n-1} (P - p^s) - c &= \bar{F}(c)^{n-1} (P - c) - c \end{aligned}$$

We are uncertain about the relationship between $\bar{F}(c)^{n-1} (P - c) - c$ and 0. As long as $\bar{F}(c)^{n-1} (P - c) - c > 0$, unique equilibrium exists. ■

Note that when $c = 0$, we know that $p^s = P$ is a

solution of (C2). This means that when there is no entry fee, all financiers will bid, given they have enough capital available.

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