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The performance of multi-type environmental credit trading markets: Lab experiment evidence

Zhi Li [a], Pengfei Liu [b,*], Stephen K. Swallow [c]

[a] MOE Key Laboratory of Econometrics, Department of Public Finance, School of Economics, the Wang Yanan Institute for Studies in Economics, and Fujian Key Lab of Statistics, Xiamen University, Xiamen, Fujian 361005, PR China

[b] Department of Environmental and Natural Resource Economics, University of Rhode Island, 1 Greenhouse Road, Kingston, RI 02881, USA

[c] Department of Agricultural and Resource Economics, Center for Environmental Sciences and Engineering , University of Connecticut, 1376 Storrs Road Unit 4021, Storrs, CT 06269, USA

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ABSTRACT

We experimentally compare the performance of two multi-type environmental credit trading markets. The first trading market is called the multiple market (MM) institution, which allows the providers to sell jointly produced credits of all types. The second trading market is called the single market (SM) institution, where the providers of jointly produced credits can only choose one type of credit to sell. We investigate several key indicators, including the trading price, quantity, and net social benefit, to compare the performance of the SM and MM institutions. We find that the trading prices are significantly lower in MM compared to SM, indicating that MM potentially benefits the credit buyers. We also find that SM leads to more credit productions. Since not all credits can be traded in SM, the increase in the production cost outweighs the increase in the total social benefit. As a result, the net social benefit is lower in SM compared to MM. We expand the literature by firstly designing a market platform for multi-type credit trading and then assessing their performance with lab experiment evidence.

1. Introduction

Environmental and ecosystem service markets establish financial incentives for the production of environmental credits. Regulations regarding the mitigation of negative environmental impacts create a demand for such environmental credits (Alston et al., 2013; Claassen et al., 2008). The current incompleteness or imperfection of environmental markets creates an ambiguity that motivates calls to regulate environmental markets. A particular form of regulation or constraint concerns “credit stacking" or “double-dipping” (Cooley and Olander, 2011; Fox, 2008). In environmental markets, credit stacking generally refers to a situation where the providers of environmental credits are allowed to sell different types of credits in separate markets, even if these credits are produced from a single management practice, likely on a single parcel of land. With credit stacking permitted, credit productions may overlap spatially for different services. The credit stacking issue partially arises from the “production complementarity” when the landowners could provide environmental benefits from the same management process (Wossink and Swinton, 2007).

From an economic perspective, disallowing credit stacking creates a restriction on trading that prevents the market from realizing full economic efficiency. However, a restricted market may not necessarily perform worse than an unrestricted market when other distortions exist, such as an incorrectly specified cap in the Cap-and-trade market (Lipsey and Lancaster, 1956). Horan et al. (2004) look at the effect of the double-dipping policy on the overall social efficiency, which depends on how the agri-environmental

* Corresponding author.
E-mail addresses: zhili@xmu.edu.cn (Z. Li), pengfei_liu@uri.edu (P. Liu), stephen.swallow@uconn.edu (S.K. Swallow).

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policy is targeted. In their context, double-dipping refers to a situation in which farmers can be paid multiple times by different programs (coordinated or not) for the same environmental improvement, which may be efficient if the aggregate marginal payment equals the marginal production cost. Woodward (2011) offers the first theoretical analysis and a quantitative simulation on the economic implications of credit stacking policies. In Woodward's model, a landowner's technology involves a complementarity and a specialization parameter in a joint production function for multiple types of environmental credits. Woodward frames credit stacking as a multiple market (MM) institution which allows the producers to sell jointly produced credits of all types, and defines an institution where credit stacking is not allowed as a single market (SM), meaning the producers of jointly produced (spatially overlapping) credits must choose one type to sell in the market. González-Ramírez and Kling (2015) extend Woodward's model and consider the influence of credit stacking policies in alternative second-best scenarios, focusing on the efficiency loss of uncoordinated policies in different environmental markets. Valcu et al. (2013) and Yeo et al. (2012) look at the environmental benefits of both carbon sequestration and water quality improvement through the same agricultural management process. Recently, Reeling et al. (2018, 2020) explore the possibility of trading different types of credits in the same market. Due to the difficulty of implementing SM and MM trading institutions in practice, there are no data available and hence no direct empirical comparisons between these two institutions. Our study advances the literature by firstly using lab experiments to demonstrate how the SM and MM trading institutions can be set up in practice and to provide empirical evidence on the trading patterns and efficiency outcomes of the two institutions.

The multiple environmental benefits from the same agricultural or environmental management process have been widely recognized. Previous studies have focused heavily on the co-benefits from the carbon credit market (Caparrós et al., 2010; Feng and Kling, 2005; Feng et al., 2007; Glenk and Colombo, 2011). The credit stacking possibility provides new opportunities to incorporate co-benefits into environmental markets. For example, landowners could sell all these environmental co-benefits in separate markets so that they would receive revenues from participating in these markets simultaneously, even though the co-benefits are the outcome of the same management practice. Allowing credit stacking, then, would be analogous to sales of jointly produced private goods, such as beef and leather from cattle. A case study on the carbon sequestration co-benefits shows that incorporating co-benefits could improve environmental outcomes and increase revenues for farmers in the Upper Mississippi River Basin based on simulation results (Feng et al., 2007), and considering co-benefits may also change the outcome of cost-benefit tests in various soil carbon sequestration programs (Glenk and Colombo, 2011). The co-benefits associated with the production of a primary environmental credit have been recognized in other markets as well, such as in the water quality credit market (Lentz et al., 2014). Liu and Swallow (2016, 2021) conduct real water quality credit transactions based on preferences for co-benefits revealed by experiment subjects and illustrate a way to incorporate public values for environmental co-benefits in the Ohio river basin water quality trading market. Results show that incorporating co-benefits in the water quality trading market leads to substantial welfare improvements.

Existing studies on credit stacking mostly use a framework of profit maximization where polluters abate several complementary pollutants (Woodward, 2011; González-Ramírez and Kling, 2015). The credit stacking issue originates from the landowners' eligibility and potential profits from simultaneously participating in multiple environmental markets by supplying environmental credits (Cooley and Olander, 2011; Fox, 2008; Valcu et al., 2013). The passage of the 1972 and 1977 Federal Water Pollution Control Act Amendments (Clean Water Act, or CWA) does not create any new permitting requirement and preserves agricultural exemptions from permitting, including normal farming practices. Therefore, unregulated landowners could produce water quality credits by improving normal management practices and receive compensations from trading water quality abatement credits to regulated parties, e.g., often to polluters who face a higher marginal abatement cost compared to landowners (Horan et al., 1999). At the same time, the landowners may potentially produce carbon credits through practices generating water quality improvements, which calls for immediate regulation attentions on landowners' eligibility to participate in either or both credit markets.

Our paper contributes to the literature in the following two perspectives. First, we experimentally test the theoretical model and insights in Woodward (2011). We find the framework proposed by Woodward (2011) has strong prediction powers on the lab experiment results. We investigate several key indicators, including the trading price, quantity, and net social benefit, to compare the performance between SM and MM. Most of our experimental results agree well with the theoretical predictions. In particular, the trading prices are significantly lower in MM than those in SM, suggesting MM could potentially benefit the credit buyers (i.e., the polluting industries). In the long term, this lower cost of abatement can create opportunities for advocates to justify more stringent pollution standards, as a cost–benefit analysis on a standard against a lower marginal abatement cost would be expected to support a higher, more stringent standard against pollution. We also find that more credits are generated in SM. However, the net social benefit is lower in SM than that in MM, since not all credits can be traded and the increase in the production cost outweighs the increase in the total social benefit in SM.

Second, we highlight several new findings with important policy implications that cannot be obtained directly from the existing theoretical framework. Unsurprisingly, we find MM generates a significantly higher net social benefit compared to SM unless the cap is set sufficiently far away from the socially optimal one. While the theoretical benchmark points out the relative advantages of MM, the experiment reveals another important advantage of MM. We find that the cost minimization potentials are not fully utilized in SM when the level of specialization in the production technology is low, which further constrains the performance of SM under certain circumstances. Our results also suggest that the trading prices are relatively more volatile in SM while the prices in MM gradually converge and stabilize quickly after the market starts.

In terms of experimental design, we implement a multi-type credit trading market experimentally based on a double auction framework (Smith and Williams, 1990; Smith, 1981; Muller et al., 2002; Stranlund et al., 2011, 2014). Our market framework can help future experimental designs on multi-type credit trading and guide the establishment of a functioning market trading framework in practice. We leverage the auction literature and illustrate how SM and MM can be set up in an experimental trading market. We find that our experimental trading market performs smoothly in expected ways. Subjects understand the rules and learn the trading mechanisms quickly in both SM and MM institutions. Though the experimental market is small in scale, our experimental test can serve as a "prototype" for a more sophisticated design for the multi-credit market trading.

The remainder of the paper is organized as follows. Section 2 introduces the experimental design and procedures, as well as hypotheses based on theoretical results. Section 3 discusses the experimental results and implications. Section 4 concludes. A sample of the experimental instruction is provided in the online appendix.

2. Experimental design and procedures

For our experiments, we envision a situation in which landowners, such as traditional agricultural producers, can modify their practices to produce two types of credits to offset pollution from regulated parties, such as sewage treatment plants or power plants. For example, farmers could choose to establish vegetated buffer strips to capture nutrients in rainwater runoff from crop-producing fields draining toward surface waters while sequestering carbon in the buffer vegetation, while other farmers may choose to alter crop selection to reduce the need for nutrient applications while intensifying sequestering carbon. These two types of landowners may have different advantages in either storing carbon or preventing nutrients from entering surface waters.

The landowners can participate in the SM or MM institution, subject to the applicability of regulatory policies. While SM imposes a restriction on landowners' choice of market participation, the potential miscoordination of environmental policies is a key limitation that leads to the SM institution. Our experiment examines how constraints on the types of tradable credits might affect cost-effectiveness or other elements of efficiency. We then evaluate the social efficiency for the case of no cap for ambient pollution (No-Cap treatment), as well as for the Cap treatment, where a permit cap below the socially optimal level has been set under the SM or MM institution. In practice, a suboptimal cap is observed quite often, due to political reasons or the uncertainty about the benefits from environmental credits, such as the social benefit of carbon reduction (Fullerton and Karney, 2018).

2.1. Experimental design

In the experiment, we simulate an environmental market where subjects trade two types of credits A and B in a computerized double auction. We assume there are two types of credit sellers (producers). A seller of type S_t is more cost-effective in producing credits of type t, where $t = A, B$. Since credits are joint products, both types of producers create some of each credit type. The cost functions for two types of sellers S_A and S_B are

$$g_i^{S_A} = \alpha Q_{A,i}^2 + \frac{1}{\alpha} Q_{B,i}^2 + \gamma Q_{A,i} Q_{B,i} \tag{1}$$

and

$$g_j^{S_B} = \alpha Q_{B,j}^2 + \frac{1}{\alpha} Q_{A,j}^2 + \gamma Q_{A,j} Q_{B,j}, \tag{2}$$

respectively, where i and j respectively denote individual sellers of type S_A and S_B, $Q_{t,l}$ denotes the quantity of credit type t produced by seller l with $t = A, B$ and $l = i, j$. The parameter $\alpha \in (0, 1)$ is the specialization level, which reflects the cost advantage of producing one type of credit relative to the other. A smaller α indicates a higher specialization level and *vice versa*. In the experiment, we compare two specialization levels, $\alpha = 0.2$ for the high specialization level and $\alpha = 0.8$ for the low specialization. The parameter $\gamma \in (-1, 0)$ represents the complementarity between the two types of credits, capturing the cost impact of one type of credits on the other. Since varying the value of γ will greatly increase the complexity of the experimental design, we fix γ at -0.5 to focus on the difference between SM and MM institutions. In addition, our choice of γ induces a more interesting case where the relative performance of SM and MM differs in the No-Cap and Cap treatments across a wide range of specialization levels based on the theoretical predictions.

We assume the social benefit function for credit type t is

$$V(Q_t) = \Omega Q_t - \frac{\theta}{2} Q_t^2 \tag{3}$$

where $t = A, B$, and Q_t represents the total quantity of credit type t produced by both types of sellers, that is, $Q_t = \sum_i Q_{A,i} + \sum_j Q_{B,i}$. We also assume the social benefit is additive in different types of credits so that the total benefits are equal to the summation of benefits from each type of credit. In the experiment, the parameter $\Omega = 45$ and the marginal social benefit parameter $\theta = 1.5$. Taking the first order derivative of the social benefit function (3), we have $V'(Q_t) = \Omega - \theta Q_t$, which represents the overall market demand for the credit of type t and is used to parameterize the buyer's demand function. In each session, we have a group of ten players, including four sellers with two for each type and six buyers. According to Eq. (3) of the social benefit function, buyer 1's marginal value is calculated by $\Omega - \theta$ for the first unit, $\Omega - (6 + 1)\theta$ for the second unit, $\Omega - (6 * 2 + 1)\theta$ for the third unit, and so on. Buyer 2's marginal value is calculated by $\Omega - 2 * \theta$ for the first unit, $\Omega - (6 + 2)\theta$ for the second unit, $\Omega - (6 * 2 + 2)\theta$ or the third unit, and so on. We calculate the marginal values for buyers 3 to 6 similarly.[1]

[1] Since the buyers need to bear all the purchasing costs, we can envision the buyers as non-profit organizations or government agencies who would incorporate public values in the credit purchases, or private industries (e.g., polluting companies) who need the credits for offsetting purposes. While purchasing credits involves public benefits, credits may be purchased by both public and private entities. The marginal values can be different between the public and private entities depending on whether the public benefits are incorporated.

Table 1
Experimental parameters and definitions.

Variables	Definition	Assigned values
α	parameter in the cost function, specialization level	0.2 (high), 0.8 (low)
γ	parameter in the cost function, complementarity level	−0.5
Ω	parameter in the benefit function	45
θ	parameter in the benefit function	1.5
Q^*	socially optimal number of credit traded	N/A
$\hat{Q}$	cap threshold where the SM and MM yield the same net benefit	N/A
A	quantity of credit A	N/A
B	quantity of credit B	N/A
P	price of the credit	N/A
Q	quantity of the credit	N/A
Variables	Experimental treatment	Equilibrium prediction
Q^*	High specialization level ($\alpha = 0.2$)	28
Q^*	Low specialization level ($\alpha = 0.8$)	26
$\hat{Q}$	High specialization level ($\alpha = 0.2$)	24
$\hat{Q}$	Low specialization level ($\alpha = 0.8$)	20
P^*	High specialization level ($\alpha = 0.2$)	3.36
P^*	Low specialization level ($\alpha = 0.8$)	6.34

Notes: This Table lists the experimental parameters, definitions, as well as theoretical predictions for Q^*, $\hat{Q}$, and P^* based on the parameters in the experiment. P^* is the equilibrium price with no market constraints.

The socially optimal quantity for each type of credit produced (and traded) can be obtained by maximizing the net benefit and is given as follows,

$$Q^* = Q_A^* = Q_B^* = \frac{\Omega(2\gamma\alpha - \alpha^2 - 1)}{\gamma^2\alpha + 2\gamma\theta\alpha - \alpha^2\theta - \alpha - \theta}. \tag{4}$$

The optimal quantity is the same for both types of credits due to the symmetry in the cost and benefit functions. Given our experimental parameters, the socially optimal quantity with the high level of specialization ($\alpha = 0.2$) is 28 and the socially optimal quantity with the low level of specialization ($\alpha = 0.8$) is 26 in each type of credit market (e.g., the market for credit A or credit B).[2]

In the experiment, we also consider trading markets with sub-optimally lower cap constraints, which are set at 85% of the optimal quantities of credits, i.e., 24 and 22 for the high and low specialization cases, respectively. With the market participation constraint, SM will not be able to trade a socially optimal level of credits while in MM, the socially optimal number of credits can be traded. There are two primary reasons for this prediction in our context. First, the SM restriction only allows firms to sell one type of credit and forbids the trading of the other type. Second, the SM restriction will change firms' optimal production decisions.[3] Therefore, we have the following hypothesis regarding the number of credits traded in the treatments with and without sub-optimal caps.

Hypothesis 1. The total number of credits traded is higher in the No-Cap treatment than in the Cap treatment. In the No-Cap treatment, the amount of credits traded is larger under MM than under SM.

Based on Eq. (3), the inverse market demand for the credit type t can be derived based on the social benefit function (3),

$$P_t = \Omega - \theta Q_t$$

where P_t and Q_t are the market price and the corresponding market quantity demanded for the credits of type $t = A, B$, respectively. Using our experiment parameters (see Table 1), the equilibrium prices are 3.36 and 6.34 at the high and low specialization levels. In MM, since the socially optimal quantity of credits Q^* can be traded, the trading prices are expected to be comparable to the equilibrium prices. In SM, however, a smaller number of credits may be traded due to the market participation constraint and higher prices are expected. Similarly, the trading prices are expected to be higher in the Cap treatment than those in the No-Cap treatment. Note that we are only able to calculate the equilibrium prices but not individual trading prices in a continuous double auction environment. Nonetheless, we expect the trading prices to follow similar patterns and to gradually converge to the market equilibrium prices. We formulate the following hypothesis regarding the credit trading price in the experiment.

Hypothesis 2. The average trading prices are higher in the Cap treatment than those in the No-Cap treatment, and the trading prices are lower under MM than those under SM due to the market participation restriction in SM.

In the Cap treatment with the cap set lower than the optimal level, there exists a unique cap

$$\hat{Q} = \frac{2\Omega\gamma}{2\theta\gamma - \theta\gamma^2\alpha - 1 + \gamma^2 - \frac{\gamma^2 - 1}{\alpha^2 + 1 - 2\gamma\alpha}} \tag{5}$$

[2] The two numbers of 28 and 26 are obtained by rounding 27.76 and 25.77 to the nearest integers.
[3] In Appendix, Figure A1 illustrates one firm's production decisions under SM and MM graphically to highlight the potential difference in the trading outcomes.

Table 2
Treatment arrangement of experimental sessions.

Sessions	Treatment 1	Treatment 2	Treatment 3	Treatment 4
S1	NC-SM-L	NC-MM-L	NC-SM-H	NC-MM-H
S2	NC-SM-H	NC-MM-H	NC-SM-L	NC-MM-L
S3	NC-MM-L	NC-SM-L	NC-MM-H	NC-SM-H
S4	NC-MM-H	NC-SM-H	NC-MM-L	NC-SM-L
S5	CP-SM-L	CP-MM-L	CP-SM-H	CP-MM-H
S6	CP-SM-H	CP-MM-H	CP-SM-L	CP-MM-L
S7	CP-MM-L	CP-SM-L	CP-MM-H	CP-SM-H
S8	CP-MM-H	CP-SM-H	CP-MM-L	CP-SM-L
S9 (replicates S5)	CP-SM-L	CP-MM-L	CP-SM-H	CP-MM-H
S10 (replicates S6)	CP-SM-H	CP-MM-H	CP-SM-L	CP-MM-L
S11 (replicates S7)	CP-MM-L	CP-SM-L	CP-MM-H	CP-SM-H
S12 (replicates S8)	CP-MM-H	CP-SM-H	CP-MM-L	CP-SM-L

Notes: This Table provides details on the treatment sequence in each experimental session.

such that the two credit markets yield the same net benefit, and MM performs better than SM in terms of the realized net social benefit when the cap is set higher than $\hat{Q}$ and *vice versa* (Woodward, 2011). Based on our experimental parameters, $\hat{Q}$ = 26.16 and 20.06 in the high and low specialization cases, respectively, for each type of credit market. Our parameters are chosen such that in the high specialization case with the Cap treatment, SM is expected to perform better than MM while in the low specialization case with the Cap treatment, MM is expected to perform better than SM. Thus, we formulate the following hypothesis regarding the performance of the two market institutions.[4]

Hypothesis 3. MM performs better than SM in terms of the net benefit except in the Cap treatment with a high specialization level using our experimental parameters.

2.2. *Experimental procedures*

To examine the experimental hypotheses, we establish a continuous double auction market with cash incentives to induce participants to value credits in a manner that simulates motivations of S_A and S_B types of credit producers. Table 1 summarizes the definitions of notations, parameters, and their assigned values in the experiment. Table 2 shows the treatment arrangement in each session. We use NC and CP to differentiate the treatment with no cap (NC) constraint and the treatment with the cap (CP) set lower than the socially optimal quantity of credits.[5] We use MM and SM to differentiate the multiple market (MM) and the single market (SM) institutions. The letters of H and L in the treatment differentiate the high (H) specialization level ($\alpha = 0.2$) and the low (L) specialization level ($\alpha = 0.8$). For example, Treatment NC-MM-H indicates that the treatment has no cap constraint and allows trading under the multiple market institution with the seller has a high specialization production technology.

We use a between-subject design for the cap constraint (NC or CP) and a within-subject design for the market institution (MM or SM) and the specialization level (H or L). Sessions S1 to S4 are for No-Cap (NC) treatments and sessions S5 to S8 are for Cap (CP) treatments with sessions S9 to S12 as a replication. There are four treatments in each session. The first two treatments are parameterized with one specialization level and the last two treatments with the other specialization level (that is, either L-L-H-H or H-H-L-L). Market institution differs for the first or last two treatments of the same specialization level. The order of market institution is the same within a session but is rotated across sessions (that is, either SM-MM-SM-MM or MM-SM-MM-SM in a complete four-treatment session). Since there are two specialization levels and two market institutions, four (2 by 2) sessions are needed to control for the order effects as used in our design for the No-Cap sessions. The number of sessions is doubled for the Cap sessions.

In the experiment, subjects are told that they would be playing with experiment tokens. The exchange rate of tokens to cash is 50 to 1 (50 tokens=$1). Subjects are then informed that they would be representing either buyers or sellers of some products. We use a more general term ‘‘product’’ instead of ‘‘environmental credit’’ or similar specific terms in the experimental instruction to avoid potential uncontrolled influences of subjective environmental attitudes. For example, Cason and Raymond (2011), Raymond and Cason (2011) find various and sometimes surprising environmental framing effects in an emissions trading experiment with voluntary compliance (see Cason (2010) for a summary). Subjects are informed about the number of sellers and buyers, their role as a buyer or seller, and their own cost or benefit information. Their role as a seller or buyer is randomly re-assigned in each period. We choose to switch the role of buyer and seller to facilitate market convergence when subjects have experience as both buyers and sellers.

Buyers are shown the values (benefits) to buy one more unit of products A and B (see Appendix for a screenshot of a buyer's interface) and need to decide whether to buy one more unit of A or/and B given the prices of the products posted in the respective markets by sellers. Buyers start with zero inventories. The maximum number of trades or inventories is provided for each type

[4] In the appendix, Table A1 summarizes the experimental hypotheses based on the theoretical derivations.

[5] In the instruction, we originally used FB (First Best) and SB (Second Best) to represent the NC (No-Cap) and CP (Cap) treatments, respectively.

of product to avoid situations where subjects incur large deficits due to over-trading.[6] Note that the marginal value indicates the benefit the subject receives from buying one more unit. Thus, a subject's profit equals the marginal value to buy one more unit of A or B minus the price accepted. Once a transaction is completed, the computer immediately shows the participants' profits from the transaction and their running totals, and the subjects can track earnings throughout the trading process.

Similarly, sellers are shown the costs to provide one more unit of products A and B and need to decide whether to produce and sell one more unit of A or B. In the multiple market (MM) setup, sellers are presented with markets of both A and B and need to determine the price to sell in each market (see Appendix for a screenshot of a seller's interface). In the Single Market (SM), sellers first need to decide which market to participate in (Market A or B).[7] The decision to participate in a market is irreversible in one trading period to be consistent with the constraint imposed in SM but subjects can choose to participate in a different market in a new trading period. After all sellers choose a market to attend, they can post the price of the product only in the chosen market but can still observe the posted prices by other sellers in both markets.[8] In SM, the seller can produce both types of products but can only sell the type of products that is consistent with the chosen market type. Sellers are also told their types of specialization determined by the parameter α as in the cost functions (1) and (2). Sellers may have a high ($\alpha = 0.2$) or low ($\alpha = 0.8$) specialization level depending on the treatment. The marginal cost to sellers changes with the unit number to be sold (i.e., unit-dependent), capturing the production complementarity in the cost function.[9]

To facilitate subjects' understanding of the cost functions, we use tables of different cost parameters to help sellers decide which market to participate in and determine the range of prices to post in the markets. For example, sellers of type S_A with a low specification are asked to refer to Table LA (in Appendix B) to make decisions. The parameter table specifies the total costs with all possible joint productions of credits A and B. The minimum numbers in each column and each row are highlighted to help subjects identify the minimum cost of producing one type of credit when the output level of the other type is fixed. Examples are explained before subjects make decisions. For example, based on Table LA, subjects are asked to find the cost to produce 9 units of A and 2 units of B (which is 60.8) and 9 units of A and 1 unit of B (which is 61.55). Then subjects are asked to consider the implications and are informed that it is possible to sell more products at a smaller cost. The area of the table bounded by the highlighted cells is shaded to indicate the efficient joint productions with the boundary included. Subjects are explicitly told that "if you sell bundles outside the highlighted cells, you are not making the best choices". However, subjects can still choose the bundles outside the efficient area without any restrictions. A seller's profit equals the accepted price minus the cost. Similar to the buyers, the profit is immediately shown to the sellers when a transaction is completed and the total profits are also summarized.

To initiate a transaction, a seller first submits a price for the product which can be seen by all buyers and sellers. A seller can submit multiple prices before a transaction is completed but cannot submit a price that is higher than the current lowest posted price. Buyers can decide whether to buy the product at the posted price. A transaction is completed once a buyer accepted the price and the trading price will be displayed on the screen for all subjects. All the outstanding asks are then cleared and sellers need to start posting prices again. The process continues until the session expires. In Treatments 1 and 2, we also included a 5-minute trial period in addition to the three market periods. There are no trial periods for Treatments 3 and 4. The outcomes in the trial periods are not counted toward the subjects' payoffs. The 5-minute time limit of a period is based on our pilot sessions and provides sufficient time for market-clearing. In the experiment, the last transaction usually ends well before the 5-minute limit.

The experiment was conducted at the University of Connecticut (UCONN) in the spring of 2018. Subjects were recruited through the UCONN Daily Digest, a central newsletter system that distributes messages to all university students daily. The number of participates per session is exactly 10, including six buyers and four sellers. Inter-participant communications during the experiment were prohibited. Subjects could not observe each others' choices. Subjects were told that they had already earned a show-up fee of $ 5 before we proceeded to the instructions. The experiment's instructions for each stage were read aloud at the start of the stage and the participants read along. Subjects were paid in cash once all treatments were finished. One experimental session usually took about one hour and forty minutes yielding an average individual payoff of around $40. The total payoff was based on accumulated profits added up across all periods except the trial periods.

3. Experimental results

Table 3 provides the summary statistics at the market level. We collect the data on 12 simulated markets for the treatments associated with the No-Cap treatment and 24 simulated markets for the treatments associated with the Cap treatment. We record a total of 6,685 completed transactions. We provide the average of the total quantity of credits traded, the average of mean, median, maximum, minimum trading prices, as well as the average market length across simulated markets separately for credit A and B. The standard deviations are included in the parentheses in the table.

In addition to the summary statistics, we provide regression evidence using both ordinary least square and random effects models based on the following specification,

$$y_{im} = \beta_0 + \beta_1 CreditType_{im} + \beta_2 SpecialH_{im} + \beta_3 No\text{-}Cap_{im} + \beta_4 MM_{im} + \beta_5 No\text{-}Cap \times MM + \eta_i + \eta_m + \epsilon_{im}, \tag{6}$$

[6] Over-trading is not observed in our experiment.

[7] See the Appendix for the instruction of Treatment NC-SM-L, Figure 1-1: Seller's screen-1.

[8] See the Appendix for the instruction of Treatment NC-SM-L, Figure 1-2: Seller's screen-2.

[9] The marginal value (benefit) to buyers is also unit-dependent.

Table 3
Summary statistics at the market level.

Market level summary statistics	High specialization				Low specialization			
	No-Cap		Cap		No-Cap		Cap	
Average of	MM	SM	MM	SM	MM	SM	MM	SM
Total Quantity of Credit A Traded	27 (1.21)	24.83 (2.95)	24 (0)	23.25 (1.29)	26.61 (1.04)	21.29 (2.36)	21.96 (0.20)	21.38 (1.21)
Total Quantity of Credit B Traded	27.91 (0.51)	22 (6.12)	24 (0)	23.04 (2.03)	26.15 (1.21)	21.21 (3.83)	22 (0)	20.37 (2.57)
Mean Trading Price Credit A	9.30 (3.53)	12.42 (4.44)	12.75 (2.3)	14.55 (2.73)	10.70 (2.30)	14.47 (3.27)	13.58 (3.55)	15.74 (2.32)
Mean Trading Price Credit B	8.64 (3.92)	14.01 (5.98)	12.37 (2.67)	15.28 (2.45)	10.18 (1.75)	14.56 (3.55)	13.50 (3.62)	15.58 (3.29)
Median Trading Price Credit A	9.01 (3.52)	12.46 (4.83)	12.62 (2.76)	14.41 (3.28)	8.91 (1.73)	13.56 (3.23)	12.75 (3.98)	15.55 (2.64)
Median Trading Price Credit B	8.40 (3.94)	14.00 (6.19)	11.68 (2.93)	15.29 (2.78)	8.78 (1.97)	13.32 (3.71)	13.06 (3.71)	15.19 (3.30)
Max Trading Price Credit A	20.15 (12.53)	22.07 (11.96)	21.95 (6.12)	24.41 (5.21)	24.87 (9.95)	24.57 (9.28)	24.96 (7.52)	25.49 (6.79)
Max Trading Price Credit B	15.25 (7.86)	23.02 (11.97)	23.66 (8.28)	23.08 (4.80)	22.23 (5.59)	31 (12.01)	22.21 (7.44)	25.28 (7.91)
Min Trading Price Credit A	3.89 (0.98)	4.8 (2.49)	6 (2.90)	7.15 (3.49)	3.8 (1.88)	8.24 (3.25)	6.80 (2.07)	8.33 (3.66)
Min Trading Price Credit B	3.44 (1.19)	7.16 (4.62)	5.78 (2.52)	8.8 (2.61)	5.07 (1.28)	8.8 (3.53)	6.67 (2.18)	8.92 (3.59)
Avg. Time to Complete Credit A Trading	3.21	3.23	2.46	2.27	4.2	4.03	2.13	3.26
Avg. Time to Complete Credit B Trading	4.38	3.47	2.64	2.28	4.2	3.95	2.46	3.57
Number of Trades Credit A	324	298	576	558	346	298	527	513
Number of Trades Credit B	335	264	576	553	340	297	528	489
Repetitions of Market	12	12	24	24	12	12	24	24

Notes: This Table provides summary statistics at the market level. The Avg. Time to Complete Credit A or B Trading is measured in minutes and indicates the time of last unit of credit A or B is traded in a market session.

where the variable $CreditType_{im}$ is a dummy variable and equals 1 if the traded credit type is A by individual i at time m, and otherwise 0. Similarly, the variables $SpecialH$, $No\text{-}Cap$, and MM are all dummy variables and equal 1 if the specialization level is high, no cap restriction (i.e., the No-Cap treatment), or the Multiple Market where subjects can sell in both markets, respectively. The variable $No\text{-}Cap \times MM$ is an interaction term to capture the differential impacts of the Cap constraint in the MM and SM institutions.

The dependent variable y_{im} either represents the quantity traded in a period or the trading price. When y_{im} represents the quantity traded in a period, the subscript i indexes the subject, and m indexes the period. There are a total of 288 observations when we group the quantity traded by period and credit type. When y_{im} represents the trading price, the subscript i indexes the subject, and m indexes the number of trades in a period. There are a total of 6,685 transaction-level observations. η_i and η_m control for the fixed effects in the OLS regressions and the random effects in the random effects model, respectively. ϵ_{im} is the error term.

Below we present experimental results based on the summary statistics and regression analyses. We first compare the number of credits traded under different treatments.

Result 1. *For each type of market, the total number of credits traded is higher in the No-Cap than that in the Cap treatment for both MM and SM. MM generates a larger amount of trading than SM in the No-Cap treatment, and the difference is not statistically significant in the Cap treatment.*

Based on our experiment parameters, the optimal number of credits traded is 28 in the high specialization case and 26 in the low specialization case for both types of credits. We impose the Cap of 24 and 22 for the high and low specialization levels in the Cap treatment, respectively. According to Table 3, our results indicate that under MM, the average total number of credits traded are 27 and 27.91 for types A and B, respectively, which are slightly lower than the optimal 28 units in the No-Cap treatment with high specialization. The average total number of credits traded are 26.61 and 26.16 for types A and B, respectively, which is slightly higher than the optimal 26 units in the No-Cap treatment with low specialization. In the Cap treatment, we find the MM leads to a total number of credits traded close to the cap with both high and low specializations. In the Cap treatment with MM, the market hits the trading cap in all the 24 simulated markets.

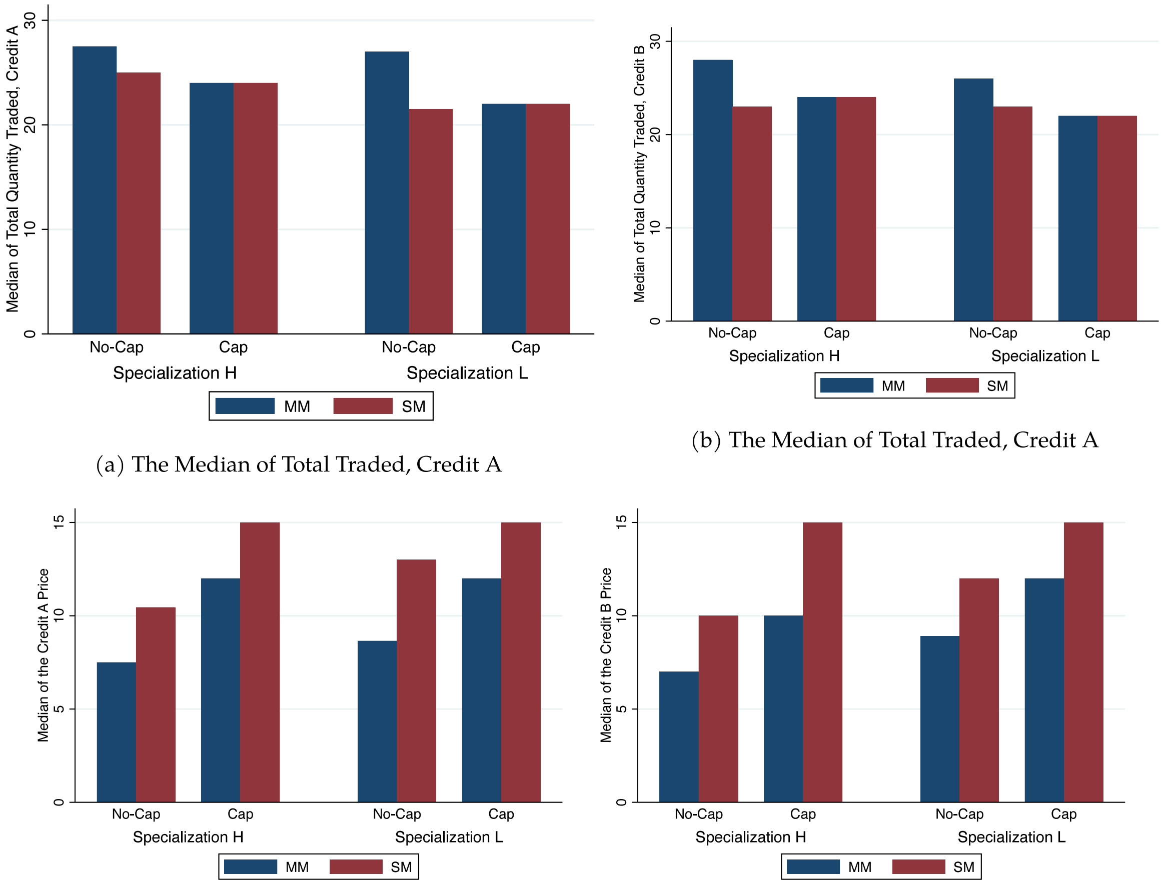
Comparing the number of credits traded in the MM and SM institutions, we find that MM consistently delivers a higher number of traded credits (for both types A and B). However, the difference between MM and SM is much larger in the No-Cap treatment and narrows in the Cap treatment. Table 4 reports the regression results using the number of credits traded as the dependent variable based on Eq. (6). Columns (1) and (2) are based on the OLS regression while columns (3) and (4) are based on the random effects model, which is our preferred specification. The interaction term *No-Cap*$\times MM$ is added to columns (2) and (3). As expected, Table 4 suggests there is no difference in terms of quantity traded between credit A and B. The high specialization level leads to a 1.964 units increase in the traded credits, which is close to the difference implied by the number of optimal traded credits. The MM leads to more units traded compared to SM; such an effect is still significant after we include the interaction term *No-Cap*$\times MM$ ($p < 0.01$). The variable *No-Cap* is not statistically significant with *No-Cap*$\times MM$ included ($p = 0.36$). Our results suggest that the MM leads to a traded amount closer to the social optimum compared to SM, under both the No-Cap and Cap treatments. In the Cap treatment, the difference between MM and SM is insignificant.

Figs. 1a and 1b compare the median number of credits traded for type A and B, respectively. Results show a similar pattern where the median number of traded credits is higher in MM in the No-Cap treatment. Such difference disappears in the Cap treatment. Our results are generally consistent with Hypothesis 1 on the number of traded credits in different treatments.

Table 4
Regression on quantity.

	(1) OLS	(2) OLS	(3) R.E.	(4) R.E.
CreditType	−0.354	−0.354	−0.354	−0.354
	(0.260)	(0.240)	(0.301)	(0.243)
SpecialH	1.965***	1.965***	1.965***	1.965***
	(0.260)	(0.240)	(0.301)	(0.243)
No-Cap	2.135***	0.323	2.135***	0.323
	(0.276)	(0.360)	(0.319)	(0.364)
MM	2.188***	0.979***	2.187***	0.979***
	(0.260)	(0.294)	(0.301)	(0.297)
No-Cap×MM		3.625***		3.625***
		(0.510)		(0.515)
Cons.	20.95***	21.56***	20.95***	21.56***
	(0.460)	(0.433)	(0.532)	(0.438)
N	288	288	288	288
adj. R^2	0.392	0.483	0.400	0.492

Notes: Standard errors are in parentheses. The dependent variable is number of credits traded at each simulated market. Regression models (1) and (2) are based on OLS regressions and models (3) and (4) are based on two-factor random effects models. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



(a) The Median of Total Traded, Credit A

(b) The Median of Total Traded, Credit A

(c) The Median of Traded Credit A Price

(d) The Median of Traded Credit B Price

Fig. 1. Number of credits traded and credit prices across different treatments. Notes: These Figures show the median number of traded credits and prices across treatments for credits A and B.

We also analyze the production outcomes by looking at the combinations of credits produced given different specialization levels. Fig. 2 shows credit production outcome combinations across different specialization levels. Observations are weighted by frequency and a larger circle presents more observations at a particular outcome combination, and *vice versa*. The red circles represent the

Table 5
Regression results on transaction price.

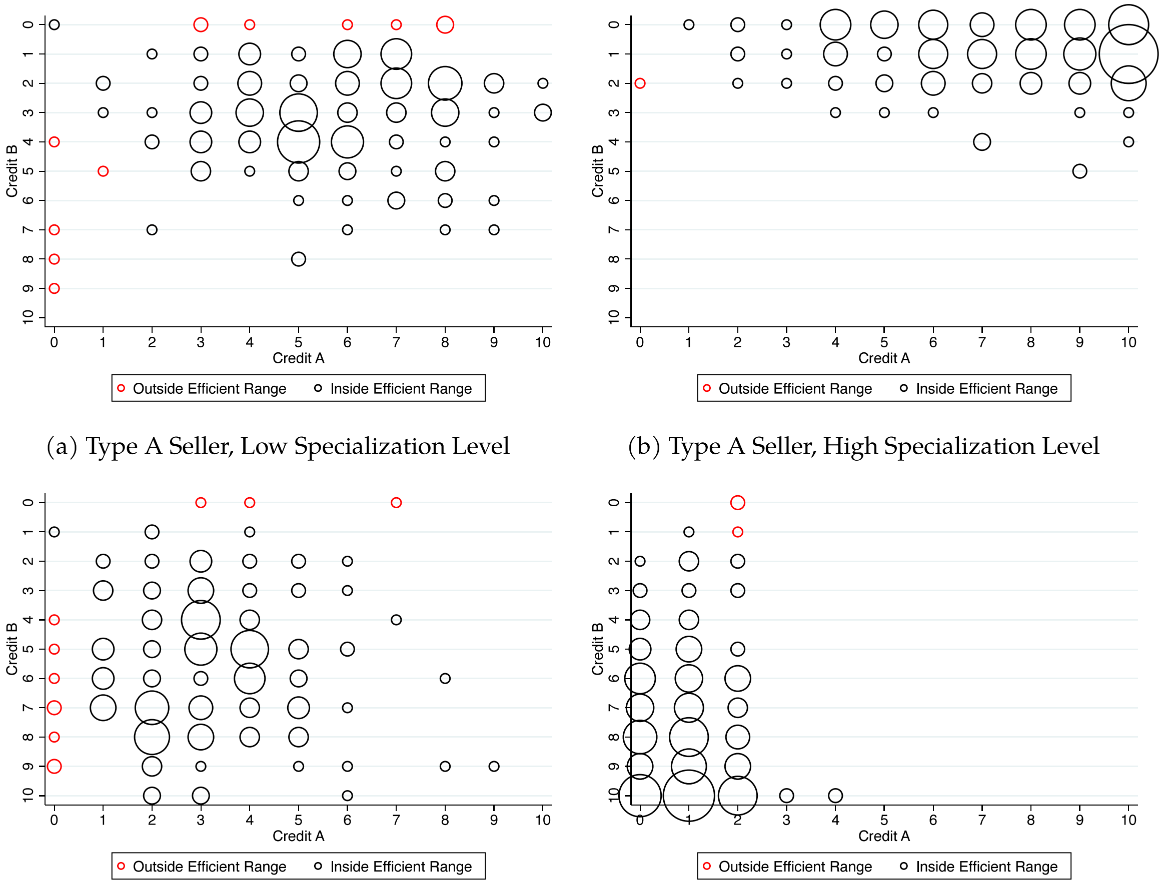
	(1) OLS	(2) OLS	(3) R.E.	(4) R.E.
Panel A: All Transactions				
CreditType	−0.0398	−0.0356	0.0534	0.0539
	(0.141)	(0.140)	(0.379)	(0.374)
SpecialH	−1.137***	−1.142***	−1.081***	−1.081***
	(0.141)	(0.140)	(0.379)	(0.374)
No-Cap	−2.516***	−1.488***	−2.353***	−1.248**
	(0.147)	(0.215)	(0.401)	(0.563)
MM	−2.860***	−2.183***	−2.964***	−2.230***
	(0.141)	(0.174)	(0.379)	(0.459)
No-Cap ×MM		−1.925***		−2.191***
		(0.294)		(0.793)
Cons.	16.21***	15.86***	16.11***	15.74***
	(0.250)	(0.255)	(0.669)	(0.675)
N	6685	6685	6685	6685
adj. R^2	0.105	0.111	0.106	0.111
Panel B: Dropping the first 10 transactions in each market				
CreditType	0.137	0.144	0.225	0.234
	(0.125)	(0.124)	(0.313)	(0.308)
SpecialH	−1.031***	−1.040***	−1.083***	−1.075***
	(0.125)	(0.124)	(0.313)	(0.308)
No-Cap	−2.876***	−1.854***	−2.708***	−1.664***
	(0.129)	(0.193)	(0.332)	(0.470)
MM	−2.905***	−2.238***	−3.097***	−2.423***
	(0.125)	(0.156)	(0.313)	(0.377)
No-Cap ×MM		−1.835***		−2.032***
		(0.258)		(0.655)
Cons.	13.83***	13.48***	13.89***	13.53***
	(0.222)	(0.226)	(0.553)	(0.556)
N	3805	3805	3805	3805
adj. R^2	0.232	0.242	0.232	0.242
Panel C: including a lagged price variable				
CreditType	0.0217	0.0231	0.0217	0.0231
	(0.101)	(0.101)	(0.101)	(0.101)
SpecialH	−0.405***	−0.409***	−0.405***	−0.409***
	(0.101)	(0.101)	(0.101)	(0.101)
No-Cap	−0.890***	−0.527***	−0.890***	−0.527***
	(0.108)	(0.155)	(0.108)	(0.155)
MM	−1.000***	−0.763***	−1.000***	−0.763***
	(0.104)	(0.127)	(0.104)	(0.127)
Price_lag	0.654***	0.652***	0.654***	0.652***
	(0.00877)	(0.00879)	(0.00877)	(0.00879)
No-Cap ×MM		−0.689***		−0.689***
		(0.212)		(0.212)
Cons.	5.204***	5.117***	5.204***	5.117***
	(0.230)	(0.231)	(0.230)	(0.231)
N	6397	6397	6397	6397
adj. R^2	0.527	0.528	0.527	0.528

Notes: Standard errors are in parentheses. The dependent variable is credit price at each transaction. Panel A includes all transactions, Panel B excludes the first 10 transactions of each simulated market, and Panel C includes a lagged price variable. Regression models (1) and (2) are based on OLS regressions and models (3) and (4) are based on two-factor random effects models. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

productions are inefficient and additional credits can be produced at a lower cost. The black circles indicate productions are within the efficient region and no additional credits can be produced at a lower cost. Results show that the majority of the production is within the efficient production region, which reduces potential concerns regarding the influences of subjects' misunderstanding on the experimental results. Subjects' production decisions are mostly rational and consistent with a profit-maximization framework.

Result 2. *The trading price is higher in SM than MM under the No-Cap treatment. The trading price is higher in the Cap compared to the No-Cap treatment, for both MM and SM institutions.*

According to Table 3, our results indicate that under the MM, the mean and median trading prices in the MM are smaller than corresponding SM scenarios. There is also no observable difference between type A and B credits in terms of price patterns. Tables 5 and A.4 in the Appendix present regression results using the trading price and log of the trading price as the dependent



(a) Type A Seller, Low Specialization Level

(b) Type A Seller, High Specialization Level

(c) Type B Seller, Low Specialization Level

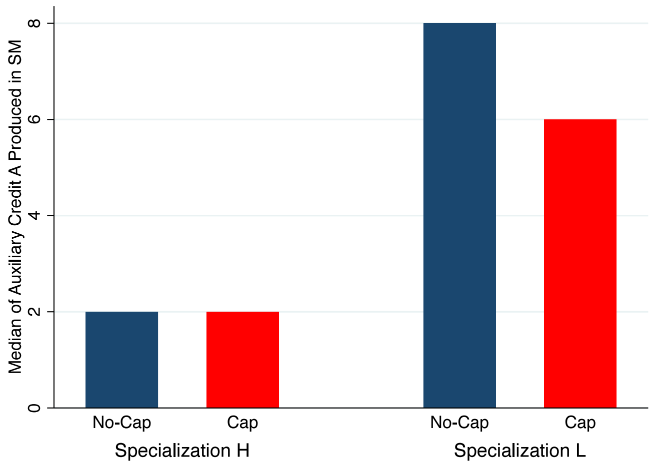
(d) Type B Seller, High Specialization Level

Fig. 2. Distribution of credit productions across different functional specifications. Notes: These Figures show credit production outcome combinations across different functional specifications. The observations are weighted by the frequency and a larger circle presents more observations at a particular outcome combination, and *vice versa*. The red circles indicate that the productions are inefficient and additional credits can be produced at a lower cost. The black circles indicate that the productions are within the efficient region and no additional credits can be produced at a lower cost. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

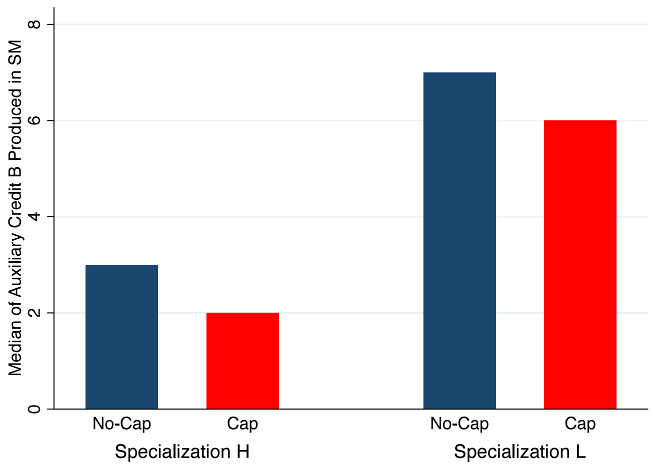
variables, respectively. Panel A includes all completed transactions. Panel B excludes the first 10 transactions in each simulated market to avoid price adjustment in early transactions. Panel C includes an additional lagged price or log lagged price variable in the specification. Our results are consistent across all specifications. The trading price is significantly lower in the No-Cap compared to the Cap treatment ($p < 0.05$ based on all transactions and $p < 0.01$ after excluding the first 10 transactions). In addition, MM leads to a significantly lower trading price compared to SM ($p < 0.01$ across all specifications). The interaction term *No-Cap×M M* is negative significant ($p < 0.01$). Excluding the first 10 transactions in each market does not alter the main results. Our results are consistent with Hypothesis 2 on the trading prices.[10] Based on Figures A2 to A5 in the Appendix, we find trading prices are subject to more adjustments at the beginning. The lagged and logged lagged price variables are positively correlated with the trading price and logged price in Tables 5 and A4, respectively. We also find that at the latter experimental periods, there are clear trends for the trading prices to converge to the market equilibrium prices in the MM, while in the SM the trading prices are more dispersed even at the end of a market period.

Result 3. *In SM, sellers choose to participate in the market for the credit type for which their production is specialized 90% of the time. Compared to a high specialization level, a low specialization level leads to more auxiliary credit production which is still below the optimal level.*

[10] In addition, no order effects are found in our regression results using the quantity and price as the dependent variables. In the Appendix, Tables A2 and A3 explicitly control for the order effects which are not statistically significant.



(a) The Median of Total Traded, Credit A



(b) The Median of Total Traded, Credit B

Fig. 3. Number of auxiliary credits traded across different treatments. Notes: These Figures compare the number of traded credits across treatments for credits A and B.

We further look at the seller's specialization and the market choice in SM. In general, type A sellers would choose market A to sell credit A and similarly for type B sellers in SM. Our results show that about 92% of type A sellers choose to participate in market A and 88% of type B sellers choose to participate in market B, suggesting that overall, about 10% of sellers choose to participate in a credit market inconsistent with their cost advantage in production. We break down the inconsistent choices by period. We find that the occurrences of inconsistent choices are 11, 14, and 18 in periods 1, 2, and 3, respectively, aggregated across all sessions, suggesting the experience does not reduce the frequency of inconsistent choices, even though the frequency is quite low in all three periods.[11]

We then summarize the number of auxiliary credits produced by specialization level and the presence of the cap constraint. Auxiliary credits refer to the credits produced under the SM institution but are not tradable due to the market participation restriction. Fig. 3 shows the median of auxiliary credits produced under different scenarios. Based on our functional form, the auxiliary credits produced can be calculated by $-\gamma\alpha Q$ when the cost is minimized, where $Q = Q^*$ in the No-Cap and $Q = \hat{Q}$ in the

[11] Note that in SM, the sellers may still produce some auxiliary credits (or so-called "free credits", "co-benefits") to reduce the cost, even though these credits cannot be traded in the market due to SM restrictions. For example, a carbon credit seller who chooses to participate in the carbon market may also produce a positive amount of water quality credit to minimize the cost, even though these water quality credits cannot be traded in the water quality market and the local water quality may be improved as a result of these auxiliary productions.

Cap treatment. The numbers of auxiliary credits are 2.6 and 2.2 in the No-Cap and Cap treatments under a high specialization level, and 11.2 and 9.6 in the No-Cap and Cap treatments under a low specialization level, respectively.

Our experimental data is largely consistent with the theoretical benchmarks, though the sellers fail to fully utilize the cost-saving opportunities when the specialization level is low. With a high specialization level, the median of auxiliary credits produced is around 2. With a high specialization level, the median of auxiliary credits produced is around 7 and ranges from 6 to 8 depending on the scenarios, which are considerably lower than the theoretical benchmarks (11.2 and 9.6 in the No-Cap and Cap treatments, respectively). A simple comparison indicates that the low specialization level is more likely to produce a larger amount of auxiliary credits or benefits under an SM restriction, though the cost-saving potentials from the joint production are not fully realized.

Result 4. *SM incurs a higher total cost and slightly higher total benefits compared to MM. MM performs better in terms of net benefit except with a high specialization under the Cap treatment, consistent with our prediction.*

We compare the realized net benefits from multi-type credit trading markets based on our functional specification and experimental data. The realized social benefit can be calculated based on Eq. (3). The total cost is the sum of individual producers cost based on the following equation

$$C = \sum_i g_i^{S_A} + \sum_j g_j^{S_B} = \sum_i \left(\alpha Q_{A,i}^2 + \frac{1}{\alpha} Q_{B,i}^2 + \gamma Q_{A,i} Q_{B,i}\right) + \sum_j \left(\alpha Q_{B,j}^2 + \frac{1}{\alpha} Q_{A,j}^2 + \gamma Q_{A,j} Q_{B,j}\right). \tag{7}$$

The net realized benefit can be calculated by the total benefits minus the total cost. Note that "credit traded" is different from "credit produced" in the SM. Since sellers need to choose a market to participate in under the SM and even if the other type of credits are produced, these credits cannot be traded. As a result, the number of credits produced is always higher than the credits traded. The difference originates from the SM restriction, where some sellers are unable to sell all types of credits. To calculate the net social benefit, we need to account for all credits produced (including the auxiliary credits) in the benefit and cost calculations.

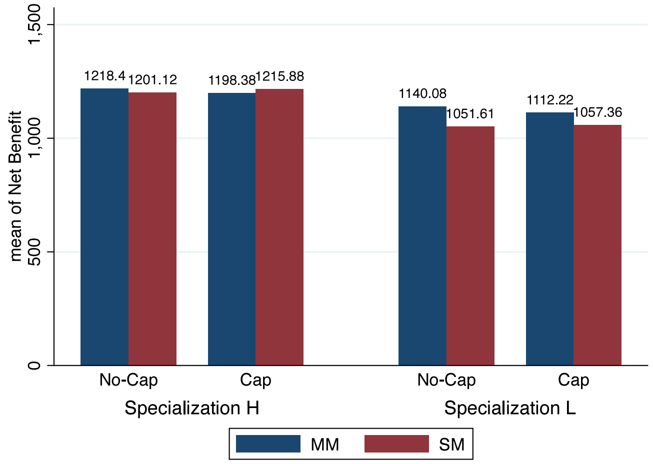
Fig. 4 presents the net benefit, total benefit, and total cost under different treatments. In the No-Cap treatment, the MM is expected to perform better than the SM in terms of net social benefit as the SM restriction prevents an optimal production decision. We show that in the No-Cap treatment, MM realizes a higher net social benefit than the SM under both high and low specialization levels. We also find the difference is smaller under a high specialization level compared to a low specialization level. Given our experimental parameters, the SM leads to 1.42% and 7.76% smaller net benefits under the low and high specialization levels, respectively. We expect similar patterns to hold in other settings.

In the Cap treatment, our caps are chosen so that SM will outperform MM with a high specialization level and MM will outperform SM with a low specialization level. Our experimental data support this prediction. We find that SM leads to a 1.46% higher net social benefit than MM when the specialization level is high and SM leads to a 4.93% lower net benefit than MM when the specialization level is low, suggesting that the cap choice is important to determine the relative advantages of SM and MM, especially when the cap cannot be chosen optimally. In Table 6, Panel A shows the regression results using the realized net benefit as the dependent variable based on both OLS and random effects models. Results show that the MM increases the net benefit significantly compared to SM at a 5% level and the increase is significant at a 10% level after we account for the potential interaction effects between the No-Cap and MM institutions. Our results are consistent with Hypothesis 3 on the performance of the two market institutions.

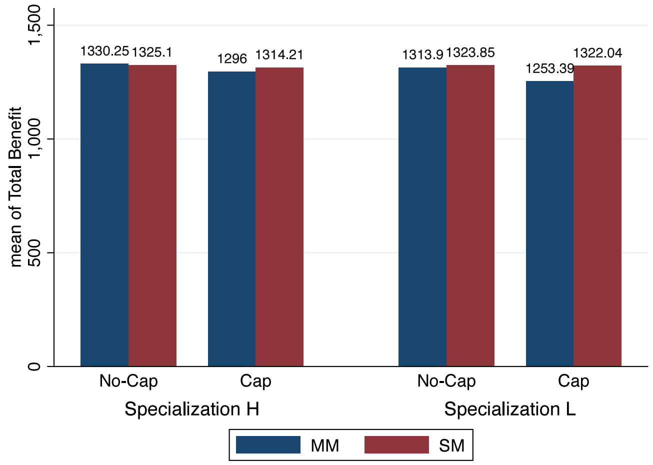
To better understand the contributing factors of the difference in net benefits, we compare the total benefits and costs separately between the MM and SM. We find that SM leads to higher total benefits except in the No-Cap with a high specialization level, due to the production of auxiliary credits. The auxiliary credits are not traded in the market but are still counted toward the total social benefits. However, once we look at the total cost comparison, the costs in the SM are also higher than the cost in the MM, especially at the low specialization level. The increase in the total cost outpaced the increase in the benefit for the SM, leading to lower net social benefits. According to Result 3, we find the cost-saving opportunities are not fully utilized in the SM under a low specialization level, further contributing to cost and net social benefits differences between SM and MM in addition to the gap predicted by theory. In Table 6, Panels B and C show the regression results using the total benefit and total cost as the dependent variables, respectively, based on both OLS and random effects models. Results show that MM leads to a significantly smaller total benefit ($p < 0.05$) as well as a significantly smaller total cost compared to SM ($p < 0.05$). Since the impact of MM on the total cost is larger compared to the total benefit, the MM results in a higher net benefit in general based on regression results.

Result 5. *Credit buyers achieve significantly higher profits, while the credit sellers obtain more or less the same profit in MM compared to SM.*

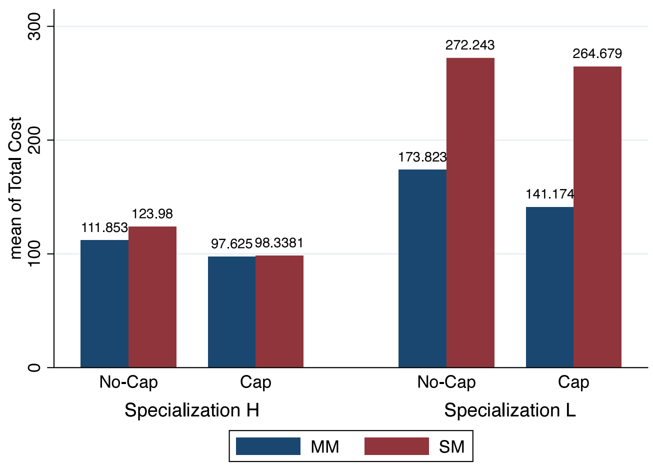
Lastly, we compare the credit buyers' and sellers' profits across different treatments, focusing on the difference between SM and MM institutions. We conduct regression analyses following a similar specification based on the regression Eq. (6) and use the seller or buyer's profit per simulated market as the dependent variable. We dropped the $CreditType$ from the set of control variables as the type variable is no longer relevant. Table 7 shows the regression results for buyers' and seller's profits in Panels A and B, respectively. Our experimental data shows the buyers benefit significantly from the MM institution across all specifications ($p < 0.01$ across all specifications), implying their compliance cost can be effectively reduced in the MM without the market participation constraint. We find a 10% profit increase for the buyers in the MM. While we expect the sellers can also benefit from MM, we do not observe a significant difference in the sellers' profits between MM and SM. The MM leads to a small but insignificant reduction in sellers' profit. Even though the market price is reduced, the ability to sell at a larger quantity offsets the price impact on revenue and the landowners' profits are more or less the same given in our experimental data. Our results also suggest that credit sellers are more likely to benefit from an incorrectly set cap compared to buyers relative to the situation when the optimal cap is known.



(a) Net Benefits across Different Treatments



(b) Total Benefits across Different Treatments



(c) Total Costs across Different Treatments

Fig. 4. Net benefit, total benefit, and total cost across different treatments. Notes: These Figures compare the net benefit, total benefit, and total cost across different treatments.

Table 6
Regression results on net benefit, total cost, total benefit.

	(1) OLS	(2) OLS	(3) R.E.	(4) R.E.
Panel A: Dependent variable is net benefit				
SpecialH	119.2***	119.1***	119.0***	119.0***
	(6.668)	(6.539)	(8.391)	(8.093)
No-Cap	6.556	−10.25	6.661	−10.25
	(6.755)	(9.346)	(8.505)	(11.58)
MM	33.26***	19.08**	33.14***	18.96*
	(6.668)	(8.584)	(8.391)	(10.61)
No-Cap ×MM		33.79**		33.91**
		(13.25)		(16.41)
	1070.0***	1077.1***	1070.0***	1077.1***
	(6.403)	(6.862)	(8.070)	(8.502)
N	144	144	144	144
adj. R^2	0.706	0.717	0.712	0.725
Panel B: Dependent variable is total benefit				
SpecialH	13.73***	13.61***	13.79**	13.74**
	(4.521)	(4.191)	(6.570)	(5.886)
No-Cap	26.94***	6.350	26.89***	6.350
	(4.581)	(5.990)	(6.662)	(8.431)
MM	−26.42***	−43.78***	−26.36***	−43.56***
	(4.521)	(5.502)	(6.570)	(7.713)
No-Cap ×MM		41.38***		41.16***
		(8.493)		(11.93)
Cons.	1302.7***	1311.3***	1302.7***	1311.3***
	(4.341)	(4.398)	(6.325)	(6.187)
N	144	144	144	144
adj. R^2	0.346	0.438	0.356	0.253
Panel C: Dependent variable is total cost				
SpecialH	−105.4***	−105.5***	−105.2***	−105.2***
	(6.572)	(6.588)	(9.451)	(9.546)
No-Cap	20.38***	16.60*	20.17**	16.60
	(6.658)	(9.415)	(9.582)	(13.68)
MM	−59.68***	−62.86***	−59.44***	−62.42***
	(6.572)	(8.647)	(9.451)	(12.51)
No-Cap ×MM		7.591		7.144
		(13.35)		(19.36)
Cons.	232.7***	234.2***	232.6***	234.1***
	(6.311)	(6.913)	(9.097)	(10.04)
N	144	144	144	144
adj. R^2	0.707	0.706	0.713	0.714

Notes: Standard errors are in parentheses. The dependent variables are net benefit, total benefit, and total cost of each simulated market in Panels A, B, and C, respectively. Regression models (1) and (2) are based on OLS regressions and models (3) and (4) are based on two-factor random effects models. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4. Conclusion

Motivated by the credit stacking issue in the environmental market, we design a multi-type credit trading market to experimentally compare the MM and SM institutions. Several key market performance indicators, such as the trading price, quantity, and net social benefit, are compared to assess the relative advantages of these two multi-type credit trading markets. We find the framework proposed by Woodward (2011) predicts the lab experiment results well. Our experimental data shows the trading prices are significantly lower in MM compared to SM, suggesting MM could potentially benefit the credit buyers, who are normally the regulated parties in the cap and trade approach to pollution or externality control. We also find that SM generates more credits. One point that is often made in favor of the MM approach is that MM will lead to more total abatements, which may not always be true and may depend on the specific production technology. However, since not all credits can be traded and the increase in the production outweighs the increase in the total social benefit, the net social benefit is lower in SM compared to MM.

Our trading framework provides ample future research opportunities. In the current experimental design, we only investigate two specialization levels and the specialization level is assumed to be fixed in a treatment. Future research could explore the influence of heterogeneous sellers on market performance. We only investigated inter-credit trading (e.g., trade the same type of credit). Recent literature has explored the possibility of cross-credit trading where different types of credits are traded in the same market (Reeling et al., 2018, 2020). It is potentially fruitful to apply our experimental framework to testing the theoretical prediction with cross-credit tradings. Lastly, our caps are exogenous. Future research can incorporate the role of a decision-maker who may set the cap endogenously based on different information and objective assumptions to more realistically mimic the real decision process.

Table 7
Regression results on Buyers' and Sellers' profits.

	(1) OLS	(2) OLS	(3) R.E.	(4) R.E.
Panel A: Dependent variable is Buyers' profit				
SpecialH	12.17***	12.10***	13.39***	13.24***
	(3.590)	(3.564)	(4.073)	(4.043)
No-Cap	24.52***	13.54***	25.37***	14.91***
	(3.637)	(5.093)	(4.113)	(5.748)
MM	33.34***	24.08***	33.48***	24.48***
	(3.590)	(4.678)	(4.067)	(5.331)
No-Cap ×MM		22.08***		21.08***
		(7.222)		(8.162)
Cons.	134.3***	138.9***	133.8***	138.4***
	(3.447)	(3.740)	(3.872)	(4.234)
N	576	576	576	576
adj. R^2	0.198	0.209	0.211	0.213
Panel B: Dependent variable is Sellers' profit				
SpecialH	17.52***	17.53***	17.11***	17.11***
	(2.597)	(2.598)	(3.008)	(3.012)
No-Cap	−16.87***	−16.24***	−17.10***	−16.68***
	(2.631)	(3.714)	(3.043)	(4.291)
MM	−3.073	−2.545	−3.103	−2.747
	(2.597)	(3.412)	(3.007)	(3.967)
No-Cap ×MM		−1.257		−0.841
		(5.264)		(6.092)
Cons.	75.14***	74.88***	74.62***	74.44***
	(2.498)	(2.732)	(2.882)	(3.165)
N	864	864	864	864
adj. R^2	0.090	0.089	0.095	0.097

Notes: Standard errors are in parentheses. The dependent variables are individual buyer's profit and seller's profit from a simulated market in Panels A and B, respectively. Regression models (1) and (2) are based on OLS regressions and models (3) and (4) are based on two-factor random effects models. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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