Adoption of a New Payment Method: Theory and Experimental Evidence*

Jasmina Arifovic[†]
Simon Fraser University

John Duffy[‡]
University of California, Irvine

Janet Hua Jiang[§]
Bank of Canada

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Abstract

We model the introduction of a new payment method that competes with an existing payment method. Due to network adoption effects, there are two symmetric pure strategy equilibria in which only one of the two payment methods is used. The equilibrium where only the new payment method is used is socially optimal. In an experiment, we find that, depending on the fixed fee for acceptance of the new payment method and on the choices made by participants on both sides of the market, either equilibrium can be selected. An evolutionary learning model provides a good characterization of our experimental data.

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[†]arifovic@sfu.ca
[‡]duffy@uci.edu
[§]jjiang@bankofcanada.ca

1 Introduction

The payments industry has undergone significant changes in the past few decades. Various new means of payments that compete with the traditional payment method – cash – have entered into the payment landscape, including debit cards, credit cards, general purpose pre-paid cards such as Visa and MasterCard gift cards, public transportation cards that expand into retail transactions such as the Octopus card in Hong Kong, mobile payments such as M-Pesa in Kenya, online money transfer schemes such as Paypal, and virtual crypto-currencies such as Bitcoin. The numerous and varied attempts to introduce new payment methods have met with mixed results. The Octopus card in Hong Kong is a notable success. Danmont in Denmark ultimately failed after a few years of limited success. Mondex debuted with much fanfare in several countries but soon failed.

In this paper we study the introduction of a new payment method, focusing on electronic pre-paid schemes. We seek answers to several questions. Will a socially more efficient new payment method take off? Can it replace the existing payment method? Will merchants accept the new payment method? How do consumers make portfolio choices between the existing and the new payment method? How do merchants and consumers interact with each other? How does the cost structure associated with the new payment system affect these results?

We first develop a model of the introduction of a new payment instrument, “e-money,” that competes with an existing payment method, "cash." We model the new payment method as being more efficient for both buyers and sellers in terms of per transaction costs. Such a cost-saving motive lies behind the various attempts to introduce a new payment method: after all, if the new payment method did not offer any such cost savings, there would be no reason to expect it to be adopted (or even introduced). There is also evidence that new developments in electronic payment technology can greatly speed up transactions and save on various handling costs associated with traditional payment methods. According to a study by Polasik et al. (2013), who analyze the speed of various payment methods from video material recorded in the biggest convenience store chain in Poland, a transaction using contactless cards in offline mode without slips costs on average 25.71 seconds, a significant reduction over a cash transaction, which costs 33.34 seconds. Arango and Taylor (2008) suggest that, after the various cash-handling costs – including deposit reconciliation, deposit preparation, deposit trips to banks, coin ordering, theft and counterfeit risk, etc. – are accounted for, a cash transaction costs merchants $0.25 and a (PIN) debit transaction costs $0.19.[1] Modelling

[1]The calculation is based on a transaction value of $36.5. The cost of the debit transaction includes a $0.12 payment-processing fee.

a force that works against the adoption of the new e-money payment method, we assume that sellers have to pay a fixed setup fee (to rent or purchase a terminal) to process the new payment method.

Given the cost structure of the two payment methods, buyers and sellers play a two-stage game. In the first stage, both types of agents make simultaneous payment decisions. Buyers allocate their budget between the existing and the new payment methods. Sellers decide whether or not to pay a fixed cost to accept the new payment method. We maintain throughout that sellers must always accept the existing payment method as a result of custom or due to legal restrictions. The second stage consists of multiple rounds of meetings where buyers and sellers trade with each other. In each meeting, the buyer observes whether or not the seller accepts the new payment method, and the trade is successful if the buyer can use a payment method accepted by the seller. Due to network effects, the model admits two symmetric pure strategy Nash equilibria. In one equilibrium, the new payment method is not adopted and all transactions continue to be carried out using the existing payment method. In the other equilibrium, the new payment method is adopted and completely replaces the existing payment method. The equilibrium involving only the new payment method is socially optimal as it minimizes total transaction costs (the reduction in per transaction cost exceeds the fixed cost paid by sellers).

As our model has multiple equilibria, we next conduct a laboratory experiment to assess conditions under which the new payment method replaces the existing payment method, and also conditions where the new payment method fails to be adopted. We find that, depending on the fixed cost for the adoption of the new payment method and on the choices made by participants on both sides of the market, either equilibrium can be selected. More precisely, if sellers face a low fixed cost to adopting the new payment method, then the new payment method is quickly adopted by all participants, while for a sufficiently high fixed cost of adoption, sellers gradually learn to refuse to accept the new payment method and transactions are increasingly conducted using the existing payment method.

We view the experimental approach as a useful complement to theoretical and empirical research on the acceptability of payment methods. The theoretical literature emphasizes the importance of network externalities in the adoption of new payment methods (Rochet and Tirole, 2002; Wright, 2003; McAndrews and Wang, 2012; Chiu and Wong, 2014). For the consumer (merchant), the benefit of adopting (accepting) a new payment method increases if more merchants accept (consumers use) that payment method. These *network effects* lead to multiple equilibria, which poses a problem for theoretical predictions, and thus our experimental study can shed some light on which equilibrium is more likely to occur. While the theory often focuses on equilibrium analysis and ignores transition dynamics, our experimental approach also provides some useful insights about the dynamic process by which a new payment method may take off and the speed with which this may occur.

Finally, we model this dynamic adjustment process using an evolutionary learning model, which provides a very good fit to the data we collected for the original three experimental treatments of our design. Indeed, the impressive fit of this learning model to our experimental data motivated us to use that model to predict design and predict outcomes for a fourth experimental treatment. We then carried out this additional experimental treatment and again report a very good fit between the evolutionary model and the experimental data.

There is a large empirical literature using survey data to explore individual choices among different means of payments.[2] Limited by the survey data available, these studies focus mainly on choices among existing payment methods and the decisions made by one side of the payment system, either the consumer or the merchant. Consumer and merchant surveys are rarely conducted concurrently, and because of high cost, usually run at a very low frequency (every few years), making it a challenging task to study the feedback effect between the two sides of the payment system.[3] For example, as discussed in Bounie, François and Van Hove (2016), empirical evidence on how consumer card usage drives merchant card acceptance is mostly indirect. To provide more direct evidence on that matter, the authors painstakingly combine three surveys conducted in France: a merchant survey in 2008, and two consumer diary surveys in 2005 and 2011. The feedback in the other direction (from merchants to consumers) has been made relatively easier thanks to improvements to recent consumer surveys to include questions on payment instruments accepted at the point of sale. Nonetheless, as pointed out in Huynh, Schmidt-Dengler and Stix (2014), special care must be taken to handle the endogeneity of card acceptance: consumers' choice of vendors may depend on the cash they have on hand.

In our model and experiment, we develop an environment suitable for the study of new payment methods that considers interactions between *both* sides of the market (buyers and sellers). We can directly investigate the feedback effect by examining how buyers respond to sellers' acceptance choices in the past and buyers' beliefs about sellers' decisions in the

[2]See, for example, Arango, Huynh and Sabetti (2016) for an analysis using the Bank of Canada 2009 Method of Payment Survey, Schuh and Stavins (2013) using the Federal Reserve Bank of Boston 2008 U.S. Consumer Payment Choice Survey, and von Kalckreuth et al. (2014) using the Deutsche Bundesbank 2008 Payment Habits in Germany Survey. Recently, Bagnall et al. (2016) studied consumers' use of cash by harmonizing payment diary surveys from seven countries. In addition to studies using survey data, other research – including Klee (2008), Cohen and Rysman (2013), and Wang and Wolman (2016) – uses scanner data to study payment choices at the point of sale. Compared with survey data, scanner data are less prone to errors and misreporting. However, scanner data are less useful for the study of payment adoption.

[3]Merchant surveys are even more scarce because it is more difficult to recruit merchants to participate in the surveys.

coming trading cycle. Similarly, we can study how sellers' acceptance decisions depend on their trading experiences with buyers in the past and sellers' beliefs about buyers' payment choices in the coming trading cycle. Further, we can examine how the decisions on the two sides co-evolve over time (which is difficult to do with field data because of the low frequency of payment surveys).[4]

The closest paper to this one is by Camera, Casari and Bortolotti (2016, hereafter CCB), who also develop a model of payment choice between cash and e-money/cards and also conduct an experimental study. While we take inspiration from CCB's paper, our project differs from theirs along several different dimensions, including the theoretical model, experimental design, research questions and experimental results. CCB study how the presence of proportional seller fees and buyer rewards affects the adoption of "card" payments, which are assumed to be more "reliable" than cash.[5] They report that sellers readily adopt card payments, regardless of the fee and reward structure, while buyers are more sensitive to these incentives. More precisely, the buyer's adoption rate is high in the absence of fees or rewards. Imposing seller fees alone reduces card adoption, but adding buyer rewards neutralizes the effect of seller fees and restores card adoption to high levels. CCB also find that there is little feedback effect between the two sides of the market so that network externalities do not matter for payment adoption. However CCB do not elicit beliefs by market participants about the likely behavior of participants on the other side of the market. Our research question is how the adoption of a new and more socially efficient payment method is affected by the fixed cost borne by sellers relative to the potential saving on per transaction costs as well as by beliefs, which we elicit. We find that choices by both buyers and sellers depend critically on the magnitude of the seller's fixed cost of adoption as well as on beliefs about what the other side of the market will do. In contrast to CCB, we find a strong feedback effect between the two sides.

The rest of the paper is organized as follows. Section 2 develops the theoretical model.

[4]Generally speaking, laboratory studies have two additional advantages over studies based on survey data. First, survey data are subject to errors due to insufficient incentives for truthful or careful reporting, or misunderstandings about the survey questions posed; these problems are alleviated to some extent in an incentivized experimental study where subjects are quizzed on their understanding of the rules prior to play. Second, since many factors are at play in the field, isolating the effect of a particular factor can be more challenging. In the laboratory, we can exert better control over the environment, thereby isolating the factors that play a role in whether or not a new payment method is adopted.

[5]CCB model e-money as more efficient in terms of per transaction cost, which is similar to our approach but in a different sense. They assume that cash payments are "manual" and consequently less reliable than electronic payments. To implement this in the laboratory, they require that buyers using cash manually click on the correct combination of bills of different denominations within a set time limit, while a card payment is quickly done with a single mouse click. While cash payments can be cumbersome, we rarely see stores turning away customers because of slow payment processing. Stores usually deal with this problem by hiring more cashiers, which we capture by having a higher per transaction cost associated with cash payments.

Section 3 describes our experimental design. The aggregate experimental results are presented in section 4. Individual buyer and seller behavior is examined in section 5. In section 6 we present an evolutionary learning model that can closely track our experimental findings and we use this model to design and predict behavior in a further experimental treatment. Finally, section 7 concludes with a summary and some directions for future research.

2 The Model

In this section, we develop a simple model of the adoption of a new payment method, "e-money," that competes with an existing payment method, "cash." In each trading period, buyers make a portfolio decision, splitting their budget between e-money and cash. Simultaneously, sellers decide whether or not to accept e-money transactions; cash payments must always be accepted. Buyers then meet with sellers and engage in transactions using one payment form or the other. For simplicity (and later experimental implementation) we assume homogeneous buyers and sellers, an exogenously given spending budget for the buyer and fixed terms of trade. As in other models of payment competition, our model has multiple equilibria.

We model the new payment method, e-money, as being more efficient for both buyers and sellers in terms of per transaction costs, but sellers must pay a fixed cost to process e-money. This setup cost, however, can be recovered if each seller succeeds in conducting a sufficient number of e-money transactions with buyers. Thus, both transaction costs and network effects play a role in decisions to adopt the new payment method. In our model, the adoption of an e-money payment method is the socially efficient outcome. We now turn to a detailed description of our model.

2.1 Physical Environment

There are large number of buyers (consumers) and sellers (firms) in the market, each of unit measure. Each seller $i \in [0, 1]$ is endowed with a technology that allows them to costlessly produce units of good i. The seller derives zero utility from consuming his/her own good and instead tries to sell his/her good to buyers. The per unit price of the good is fixed at 1, which is also the seller's utility gain from each transaction. In each period, each buyer $j \in [0, 1]$ visits all sellers in a random order, and would like to purchase and consume one and only one unit of each good produced by each seller. The buyer is endowed with just enough income to make the desired purchases. The buyer's utility from consuming each good is u.

There are two payment instruments: cash and e-money; we sometimes refer to the latter as "cards."[6] Each cash transaction incurs a cost, τ_b, to buyers, and a cost, τ_s, to sellers. The per transaction costs for e-money are τ_b^e and τ_s^e for buyers and sellers, respectively. Sellers have to pay an up-front cost, $F > 0$, that enables them to accept e-money payments, for example, to rent or purchase a terminal to process e-money transactions.

In the beginning of each trading period, sellers decide whether or not to accept e-money at the one-time fixed cost of F. Cash, being the traditional (and legally recognized) payment method, is universally accepted by all sellers. Simultaneous with the sellers' decision, buyers make a portfolio choice as to how to divide their income endowment between cash and e-money. After sellers have made their acceptance decisions and buyers have made their portfolio decisions, the buyers then go shopping, visiting all of the stores in a random order. When a buyer enters store i, he buys one unit of good i if the means of payment s/he currently has available are accepted by the seller. Otherwise, there is no trade. At the end of the trading period, sellers spend their money balances on a general good. One unit of the general good costs one dollar and entails one unit of utility. Buyers do not wish to consume the general good and any unspent money does not yield them any extra utility.[7]

In what follows, we make the following four assumptions about costs:

A1: $\tau_b^e < \tau_b$ and $\tau_s^e < \tau_s$. In words, e-money saves on per transaction costs for both buyers and sellers.

A2: $u - \tau_b > 0$. Under this assumption, buyers prefer cash trading to no trading.

A3: $F \leq \tau_s - \tau_s^e + \tau_b - \tau_b^e$. This condition implies that the net benefit of investing in the ability to process e-money transactions is positive for the society if all transactions are carried out in e-money.

A4: $F \leq 1 - \tau_s^e$. This assumption ensures the existence of an equilibrium where only e-money is used.

[6]By "card" we mean a pre-paid payment card or a debit card; we are not considering credit cards to be e-money/cards as credit cards allow unsecured debt, which would complicate our analysis.

[7]The assumptions that sellers do not value their own goods and buyers do not value the general good are for simplicity. The model's implications do not hinge on these assumptions.

2.2 Equilibrium

We will focus on symmetric equilibria, where all buyers make the same portfolio choice decision, and all sellers make the same e-money acceptance decisions. Let $0 \leq m_b \leq 1$ be the e-money balance chosen by the buyer, and let $0 \leq m_s \leq 1$ denote the fraction of sellers who accept e-money. If $0 < m_s < 1$, then sellers play a mixed strategy, accepting e-money with probability m_s.

2.2.1 Buyer's Decision

We will first analyze the buyer's decision, m_b, conditional on the seller's adoption decision, m_s. We will carry out the analysis in two cases: (1) $m_b \geq m_s$, and (2) $m_b \leq m_s$.

If $m_b \geq m_s$, then each buyer makes m_s purchases using e-money and $1 - m_b$ purchases using cash. Buyers are not able to transact with a fraction $m_b - m_s$ of sellers because of payment mismatches (buyers want to use e-money but sellers only accept cash). The buyer's expected payoff in this case is:

$$\pi_b = \underbrace{m_s(u - \tau_b^e)}_{\text{e-money transaction}} + \underbrace{(1 - m_b)(u - \tau_b)}_{\text{cash transaction}}.$$

Note that

$$d\pi_b/dm_b = -(u - \tau_b) < 0.$$

It follows that for this case, the optimal choice of each buyer is to reduce m_b to m_s so as to minimize the probability of a payment mismatch or no trade outcome.

If $m_b \leq m_s$, then each buyer makes m_b e-money transactions and $1 - m_b$ cash transactions (among which $m_s - m_b$ are with sellers who also accept e-money). The buyer's expected payoff is now given by:

$$\pi_b = \underbrace{m_b(u - \tau_b^e)}_{\text{e-money transaction}} + \underbrace{(1 - m_b)(u - \tau_b)}_{\text{cash transaction}}.$$

In this case we have that

$$d\pi_b/dm_b = -\tau_b^e + \tau_b > 0.$$

Thus, if $m_b \leq m_s$, then buyers should increase their e-money balances to m_s so as to minimize transaction costs.

From the analysis above it follows that buyers' optimal portfolio decision is to mimic the sellers' acceptance decision:

$$m_b(m_s) = m_s.$$

2.2.2 Seller's Decision

We now turn to the seller's acceptance decision conditional on the buyer's portfolio decision, m_b. We will carry out our analysis under two parameter settings: (1) $F \leq \tau_s - \tau_s^e$, and (2) $F \geq \tau_s - \tau_s^e$. For each parameter setting, similar to the discussion of the buyer's choice, we analyze the seller's decision in two cases: $m_b \geq m_s$ and $m_b \leq m_s$.

Parameter Setting (1): $F \leq \tau_s - \tau_s^e$. If $m_b \geq m_s$, then each seller who accepts e-money engages in a unit measure of e-money transactions (remember that buyers use e-money whenever the seller accepts it), and has a payoff of

$$\pi_s^e = 1 - \tau_s^e - F.$$

Sellers who only accept cash engage in an average of $(1-m_b)/(1-m_s) \leq 1$ cash transactions (the total cash balance in the economy is $1 - m_b$ and this is divided among the $1 - m_s$ sellers who only accept cash). Sellers who only accept cash thus have a payoff of

$$\pi_s = \frac{1 - m_b}{1 - m_s}(1 - \tau_s).$$

In this case,

$$\begin{aligned}(\pi_s^e - \pi_s)|_{m_b \geq m_s} &= 1 - \tau_s^e - F - \frac{1 - m_b}{1 - m_s}(1 - \tau_s) \\ &= (\tau_s - \tau_s^e - F) + \frac{(1 - \tau_s)(m_b - m_s)}{1 - m_s}.\end{aligned}$$

As long as $m_b > m_s$, we have $\pi_s^e > \pi_s$, i.e., each seller who accepts e-money is able to trade for e-money in all meetings, which makes it profitable to pay the fixed cost, F, to accept e-money. As a result, π_s will increase. In equilibrium, it must be the case that $m_b \leq m_s$.

If $m_b \leq m_s$, the e-money balance in the economy can support m_b e-money transactions, which are divided among m_s sellers who accept e-money. Each seller who accepts e-money can trade in all meetings, among which m_b/m_s will be e-money transactions, and the remaining $1 - m_b/m_s$ will be cash transactions. The expected payoff of a seller who accepts e-money is therefore:

$$\begin{aligned}\pi_s^e &= \underbrace{\frac{m_b}{m_s}(1-\tau_s^e)}_{\text{e-money transaction}} + \underbrace{\left(1-\frac{m_b}{m_s}\right)(1-\tau_s)}_{\text{cash transaction}} - F \\ &= (1-\tau_s) + \frac{m_b}{m_s}(\tau_s - \tau_s^e) - F.\end{aligned}$$

Sellers who only accept cash engage in cash transactions in all meetings and have a payoff of

$$\pi_s = 1 - \tau_s.$$

In this case,

$$(\pi_s^e - \pi_s)|_{m_b \le m_s} = \frac{m_b}{m_s}(\tau_s - \tau_s^e) - F.$$

If $m_b \ge F/(\tau_s - \tau_s^e)$, then it is a dominant strategy for sellers to accept e-money: each seller makes more than $F/(\tau_s - \tau_s^e)$ e-money sales to warrant the fixed investment for e-money acceptance. If $m_b \le F/(\tau_s - \tau_s^e)$, the number of e-money transactions is not large enough to recover the fixed acceptance cost for all sellers. As a result, sellers play a mixed strategy: $m_s = m_b(\tau_s - \tau_s^e)/F$ fraction of sellers accept e-money, and the rest accept cash only. All sellers earn the same expected payoff ($\pi_s = \pi_s^e$).

To summarize, if $F \le \tau_s - \tau_s^e$, then given the buyer's strategy m_b, the seller's strategy is such that

$$m_s(m_b) = \begin{cases} \frac{m_b(\tau_s - \tau_s^e)}{F} & \text{if } m_b \le \frac{F}{\tau_s - \tau_s^e}, \\ 1 & \text{if } m_b \ge \frac{F}{\tau_s - \tau_s^e}. \end{cases}$$

Note that if $F = \tau_s - \tau_s^e$, then $m_s(m_b) = m_b$.

Parameter Setting (2): $F > \tau_s - \tau_s^e$. Suppose $m_b < m_s$, sellers who do not accept e-money earn a higher payoff (i.e., $\pi_s^e - \pi_s < 0$). As a result, m_s will decrease. In equilibrium, it must be the case that $m_b \ge m_s$.

If $m_b \ge m_s$, it is a dominant strategy for sellers not to accept e-money if $m_b \le \hat{m}_b \equiv 1 - [(1-\tau_s^e) - F]/(1-\tau_s)$. If $m_b \ge \hat{m}_b$, then sellers play a mixed strategy, choosing to accept with probability $m_s(m_b) = 1 - (1-m_b)(1-\tau_s)/[(1-\tau_s^e) - F]$, which solves $(\pi_s^e - \pi_s)|_{m_b \ge m_s} = 0$.

To summarize, under the parameter setting $F > \tau_s - \tau_s^e$, given the buyer's strategy m_b, the seller's strategy is such that

$$m_s(m_b) = \begin{cases} 0 & \text{if } m_b \leq 1 - \frac{(1-\tau_s^e)-F}{1-\tau_s}, \\ 1 - \frac{(1-m_b)(1-\tau_s)}{(1-\tau_s^e)-F} & \text{if } m_b \geq 1 - \frac{(1-\tau_s^e)-F}{1-\tau_s}. \end{cases}$$

2.2.3 Equilibrium

Combining the analysis above, we can characterize the symmetric equilibrium of the economy using Figure 1. There are at least two symmetric pure strategy equilibria. In one of these equilibria, $m_b = m_s = 1$: all sellers accept e-money, and all buyers allocate all of their endowment to e-money – call this the all-e-money equilibrium (this equilibrium always exists provided that $F \leq 1 - \tau_s^e$). There is a second symmetric pure strategy equilibrium where $m_b = m_s = 0$ and e-money is not accepted by any seller or held by any buyer – call this the all- cash equilibrium. In both equilibria, there is no payment mismatch, and the number of transactions is maximized at 1. In the case where $F = \tau_s - \tau_s^e$, there exists a continuum of possible equilibria in which $m_s \in (0, 1)$ and $m_b = m_s$.

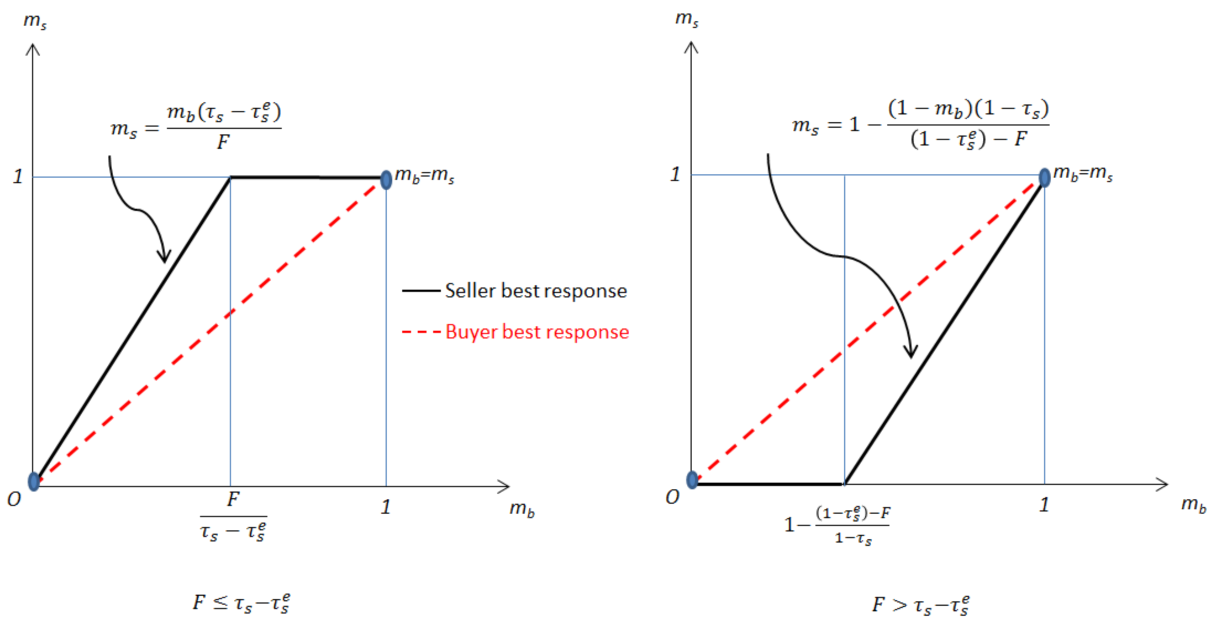
The e-money equilibrium is socially optimal as it minimizes total transactions cost. Note that buyers are always better off in the all- e-money equilibrium relative to the all cash equilibrium. The seller's relative payoff in the two equilibria, however, depends on the fixed cost, F, and on the savings on per transaction costs from the use of payment 2. If $F = \tau_s - \tau_s^e$, then the seller's payoff is the same in the cash and e-money equilibria; if $F < \tau_s - \tau_s^e$, then the seller's payoff is higher in the e-money equilibrium than in the cash equilibrium; finally, if $F > \tau_s - \tau_s^e$, then the seller's payoff is lower in the all e-money equilibrium than in the all cash equilibrium.

3 Experimental Design

The experiment was designed to match the model as closely as possible, but without the continuum of buyers and sellers of unit mass. Specifically, for each session of our experiment, we recruited 14 inexperienced subjects and randomly divided them up equally between the buyer and seller roles, so that each market had exactly seven buyers and seven sellers. These roles were fixed for the duration of each session to enable subjects to gain experience with a particular role. The subjects then repeatedly played a market game that approximates the model presented in the previous section.

Specifically, subjects participated in a total of 20 markets per session. Each market con-

Figure 1: Symmetric Equilibria



sisted of two stages. The first stage was a payment choice stage. In this first stage, each buyer was endowed with seven experimental money (EM) units (as there were 7 sellers) and these buyers had to decide how to allocate his/her seven EM between the two payment methods. To avoid any biases due to framing effects, we used neutral language throughout, referring to cash as "payment 1" and e-money as "payment 2". Thus, in the first stage, buyers allocated their 7 EM between payment 1 and payment 2, with only integer allocation amounts allowed, e.g., 3 EM in the form of payment 1 and 4 EM in the form of payment 2.[8] Each seller was endowed with seven units of goods (as there were seven buyers). Sellers were required to accept payment 1 (cash) but had to decide in this first stage whether or not to accept payment 2 (e-money) for that market. Sellers who decided to accept payment 2 had to pay a one-time fixed fee of T EM per market that enabled them to accept payment 2 in all trading rounds of that market. As explained below, T is related to the fixed costs of adopting the new payment method (F) described in the model and serves as our main experimental treatment variable.

In addition to making payment choices in the first stage, subjects were also asked to forecast other participants' payment choices for that market. We elicited these forecasts because we wanted to better understand subjects' decision-making process. Specifically, buyers were asked to forecast how many of the seven sellers would choose to accept payment 2 in the forthcoming market. Sellers were asked to supply two forecasts: (1) the average amount of the seven EM units that all seven buyers would allocate to payment 2, and (2) how

[8]The restriction of the strategy space to integer allocations was to facilitate the construction of payoff tables.

many of the other six sellers would choose to accept payment 2 in the forthcoming market. Forecasts were incentivized; subjects earned 0.5 EM per correct forecast in addition to their earnings from buying/selling goods (also in EM). The seller's forecast of the average amount of EM that buyers had allocated to payment 2 was counted as correct if it lay within ± 1 of the realized value. The other two forecasts were counted as correct only if they precisely equaled the realized value.[9] Note that no participant observed any other sellers' or buyers' payment choices or forecasts in this first stage; that is, all first stage choices and forecasts were private information and were made simultaneously.

Following completion of the first stage of each market, play immediately proceeded to the second, "trading" stage of the market, which consisted of a sequence of seven trading rounds. In these seven rounds, each subject anonymously met with each of the seven subjects who was in the opposite role to him/herself, sequentially and in a random order. In each meeting, the buyer and seller tried to trade one unit of good for one unit of payment (recall that the terms of trade in our model are fixed). Specifically, when each buyer met each seller (and not earlier), the buyer learned whether the seller accepted payment 2 or not, and then the buyer alone decided which payment method to use, conditional on the buyer's remaining balance for that market of either payment 1 or payment 2. Sellers were passive in these trading rounds, simply accepting payment 1 from the buyer or payment 2 if the seller had paid the one-time fee to accept payment 2 in that market, depending on the choice of the buyer. Thus, provided that a buyer had some amount of a payment type that the seller accepted, trade would be successful. For each successful transaction, both parties to the trade earned 1 EM less some transaction costs for the trading round, where the transaction costs depended on whether payment 1 or 2 was used, as detailed below.[10] Notice that the only instances in which a transaction could not take place (was never successful) were those in which the buyer had only payment 2 and the seller did not accept payment 2. In those cases, no trade could take place and both parties earned 0 EM for the trading round.

Following completion of the seven trading rounds of the second stage of a market, that market was over. Provided that the 20th market had not yet been completed, play then pro-

[9]We chose this incentive scheme in the interest of simplicity as belief elicitation was not the main focus of our experiment, and we did not want to devote time to explaining more complicated elicitation procedures involving proper scoring rules.

[10]Note that while buyers were endowed with 7 EM at the start of each market, this endowment had to be allocated between payment 1 and payment 2 for the buyers to actually earn EM in each of the seven trading rounds of the second stage of the market. Buyers could *not* choose to refuse to engage in trade and redeem their endowment of EM. At the end of each market, unused allocations of EM to either payment method had no redemption value. Further, EM endowments and payments earned were not transferable to subsequent markets. Instead, earnings were recorded and paid out only at the end of the experiment following the completion of the 20th market. Thus, buyers started each new market with exactly 7 EM and had to make payment allocations and payment choices anew in each market in order to earn EM in that market.

ceeded to a new two-stage market wherein buyers and sellers had to once again make payment choices and forecasts in the first stage and then engage in seven rounds of trading behavior in the second stage. Buyers were free to change their payment allocations and sellers were free to change their payment 2 acceptance decisions from market to market but only in the first stage of the market; the choices made in this first stage were then in effect for all seven rounds of the second trading stage of the market that followed. Thus, in total there were 20 markets involving seven trading rounds each or a total 140 trading rounds per session. In each trading round subjects could earn as much as 1 EM ($u = 1$)less transaction costs, and in the first stage, they could earn 0.5 EM per correct forecast. Following completion of the 20th market, subjects were paid their cumulative EM earnings from all rounds of all markets at the known and fixed rate of 1 EM = 0.15 cents, and in addition they were paid a $7 show-up payment. Each session lasted for about two hours. The average earnings were between $\$15$ and $\$25$.

To facilitate decision making, we provided subjects with two pieces of information in stage 1, at the same time that buyers were asked to make their payment allocation choices and sellers were asked to make their payment 2 acceptance decisions and both types had to form forecasts as described above. The first piece of information provided to subjects consisted of payoff tables. The buyer's payoff table reported the buyer's market earnings if the buyer allocated between 0~7 EM to payment 2 (and his/her remaining EM to payment 1) and if 0~7 sellers accepted payment 2. The seller's payoff table reported the expected market earnings the seller could get from the two options (accept/reject payment 2) in cases where *all* buyers choose to allocate between 0~7 EM to payment 2, and where 0~6 of the other six sellers choose to accept payment 2.[11] In addition to these payoff tables, sellers also had access to a "what if" calculator that computed their expected earnings in asymmetric cases where the seven buyers made different payment allocation choices. The second piece of information that we provided subjects in stage 1 (beginning with market 2 and every market thereafter) was a history of outcomes in all past markets, including the subject's payment choice, the number of transactions using each of the two payment methods, the number of no-trade meetings, market earnings from trading, and the number of their correct forecasts. In addition, we reported an aggregate market-level statistic: the number of sellers who had chosen to accept payment 2 in the prior market. We provided the latter information so that sellers could learn about other sellers' payment 2 acceptance decisions in the just completed market; since all buyers visit all sellers and learn whether each seller accepts payment 2 or not, buyers had this economy-wide piece of information by the end of each market. By

[11]See the experimental instructions in Appendix C, which includes the payoff tables for both the buyers and the sellers.

providing this same information also to sellers, we made sure that both sides of the market had symmetric information about seller choices.

For simplicity, we set the per transaction cost to be the same for all buyers and sellers, i.e., $\tau_b = \tau_s = \tau = 0.5$ for payment 1, and $\tau_b^e = \tau_s^e = \tau^e = 0.1$ for payment 2. Thus, consistent with assumption A1, it was always the case that $\tau - \tau^e = 0.4$ in all treatments of our experiment. We also set the utility gained from a sale or purchase, $u = 1$, so that consistent with assumption A2, $u - \tau > 0$. Our only treatment variable was the once-per-market fixed cost, T, that each seller had to pay to accept payment 2, which corresponds to the parameter F in the model with a continuum of agents via the transformation $T = 7F$. We initially chose three different values for this main treatment variable: $T = 1.6$, 2.8, and 3.5, respectively.[12] Later, in section 6 we consider a fourth value for this treatment variable, $T = 4.5$.

Note that, given the lower transaction cost from using e-money, buyers are always better off in the all-e-money (all-payment-2) equilibrium relative to the all-cash (all-payment-1) equilibrium. However, sellers' relative payoffs depend on the fixed cost, T. If $T < 7(\tau - \tau^e)$, as in our $T = 1.6$ treatment (and represented graphically in the left panel of Figure 1), then the seller's payoff (like the buyer's payoff) is higher in the all-e-money equilibrium than in the all-cash equilibrium. If $T > 7(\tau - \tau^e)$, as in our $T = 3.5$ treatment (and represented graphically in the right panel of Figure 1), then the seller's payoff is lower in the all-e-money equilibrium than in the all-cash equilibrium. Finally, if $T = 7(\tau - \tau^e)$, as in our $T = 2.8$ treatment, then the seller's payoffs are the same in both the cash and e-money equilibria. Table 1 reports the net payoffs (in EM) per market, that buyers and sellers earn in the two pure strategy equilibria of each treatment. As this table reveals, the sum of buyers and sellers net (of transaction cost) payoffs is always greater in the all-payment-2 equilibrium as compared with the all-payment-1 equilibrium so that the all-payment-2 equilibrium is always the socially optimal equilibrium.

[12] The ratio $\tau/\tau^e = 5$ and the various values for the fixed cost, T, were chosen to make the transaction and setup cost differences sufficiently salient to our subjects (in terms of their earnings) and are not meant to be empirically accurate, though card transaction costs *are* lower than cash transaction costs as mentioned in the introduction and seller setup costs for card adoption are non-zero and do vary.

Table 1: Payoffs

	All-payment-1 equilibrium			All-payment-2 equilibrium		
T	Buyer	Seller	Sum	Buyer	Seller	Sum
1.6	3.5	3.5	7	6.3	4.7	11
$2.8 = 7(\tau - \tau^e)$	3.5	3.5	7	6.3	3.5	9.8
3.5	3.5	3.5	7	6.3	2.8	9.1

In terms of theoretical predictions, under all of our different treatment conditions, there always exist two symmetric pure strategy Nash equilibria, one in which no seller accepts payment 2 and all buyers allocate all of their endowment to payment 1 (the all-cash equilibrium) and another such equilibrium in which all sellers accept payment 2 and all buyers allocate all of their endowment to payment 2 (the all-e-money or card equilibrium). Given our parameterization, the symmetric payment 2 equilibrium is always the one that maximizes social welfare.

While our focus is on symmetric equilibria, we note that there may also exist *asymmetric* equilibria where some fraction of sellers accept payment 2 while the remaining fraction do not, and buyers adjust their portfolios of payment 1 and 2 so as to perfectly match this distribution of seller choices. These asymmetric equilibria are always present in the $T = 2.8$ treatment, where $T = 7(\tau - \tau^e)$. In particular, any outcome where $m_s \in \{1, 2, ..., 6\}$ sellers accept payment 2, while $7 - m_s$ do not, and all buyers allocate the same m_s units of their endowment to payment 2 and $7 - m_s$ to payment 1 comprises an asymmetric equilibrium for this treatment. These asymmetric equilibrium characterize dual payment outcomes, where *both* cash and e-money are used to make transactions. Because of our use of a finite population size of 14 subjects, there are also some asymmetric pure strategy equilibria of this same variety in the $T = 1.6$ and $T = 3.5$ treatments. However, these asymmetric equilibria are fewer in number than in the $T = 2.8$ treatment and they would disappear completely as the population size got larger and we approached the continuum of the theory, whereas the set of asymmetric equilibria in the $T = 2.8$ case would continue to grow and would eventually reach a continuum, as in the theoretical model.

This multiplicity of equilibrium possibilities motivates our experimental study; equilibrium selection is clearly an empirical question that our experiment can help to address. We hypothesize that, as the transaction cost to sellers of accepting payment 2 increases from $T = 1.6$ to $T = 2.8$ and on up to $T = 3.5$, coordination on the e-money equilibrium will become less likely and coordination on the cash equilibrium will become more likely; however, this remains an empirical question. In addition, we are interested in understanding the dynamic process of equilibrium selection in terms of the evolution of subjects' beliefs and choices.

The experiment was computerized and programmed using the z-Tree software (Fischbacher, 2007). At the beginning of each session, each subject was assigned a computer terminal, and written instructions were handed out explaining the payoffs and objectives for both buyers and sellers. See Appendix C for example instructions used in the experiment. The instructor read these instructions aloud in an effort to make the rules of the game public knowledge. Subjects could ask questions in private and were required to successfully complete a quiz to check their comprehension of the written instructions prior to the start of the first market. Communication among subjects was prohibited during the experiment.

We have four sessions for each of our three original treatment conditions, $T = 1.6$, $T = 2.8$ and $T = 3.5$. As each session involved 14 subjects with no prior experience participating in our study, we have data from $4 \times 3 \times 14 = 168$ subjects. The experiment was conducted in two locations: Simon Fraser University (SFU), Burnaby, Canada, and at the University of California, Irvine (UCI), USA, using undergraduate student subjects. Specifically, two sessions of each of our three treatments (one-half of all sessions) were run at SFU and UCI, respectively. Our aim in conducting the experiment at two different locations was to assess whether our results would replicate with different subject pools and experimenters conducting the sessions. Despite our use of these two different subject pools, we did not find significant differences in either buyer or seller behavior across these two locations, as we show later in the paper.

4 Aggregate Experimental Results

In this section, we present and discuss our experimental results at the aggregate level. The next section will address individual behavior.

Figures 2a, 2b and 2c show the time series on payment choices and transaction methods in each of the four sessions of our three treatments. In all of these figures, the horizontal axis indicates the number of the market, running from 1 to 20. Each figure has two panels. In the first panel the series labeled "BuyerPay2," shows the percentage of the endowment that all buyers allocated to payment 2 averaged across the seven buyers of each session. In this same panel, the percentage of sellers accepting payment 2 is indicated by the series labeled "SellerAccept." The second panel of Figures 2a, 2b and 2c show three time series: (1) the frequency of meetings that resulted in transactions using payment 1 labeled as "Pay1," (2) the frequency of meetings that resulted in transactions using payment 2 labeled as "Pay2," and

(3) circles indicating the frequency of no-trade meetings labeled as "NoTrade."

Tables 2 and 3 display various statistics for each of the 12 sessions of the experiment. For each statistic, we show the treatment-level average in bold face. Table 2 provides five statistics on payment choice and usage and transactions. The first part (rows 1 to 10) of Table 2 reports the percentage of endowment allocated to payment 2 averaged across the seven buyers and the percentage of the seven sellers accepting payment 2. In particular, we report the session mean, minimum and maximum, and the mean in the first and the last markets for these two statistics. The second part of Table 2 (rows 16 to 25) shows the percentage of meetings that resulted in trading with payment 1, trading with payment 2 and no trading in a market. Again, we provide the session mean, minimum and maximum, and the mean value in the first and last markets for these statistics. Table 3 provides the same set of statistics on payoff efficiency for buyers, sellers or both ("all"), measured as a percentage of the payoffs that could be earned in the all-payment-2 equilibrium and the all-payment-1 equilibrium.

Finding 1 *Across the three treatments, as T is increased from 1.6 to 2.8 to 3.5, there are significant decreases in the buyer's choice of payment 2, the seller's acceptance of payment 2, and successful transactions involving payment 2.*

Support for Finding 1 comes from Table 4, which reports results from a Wilcoxon rank-sum test of treatment differences using session level averages (four per treatment). The test results indicate that the buyer's choice of payment 2 (BuyerChoice), the seller's acceptance of payment 2 (SellerAccept) and successful payment 2 transactions (Pay2Meetings) are significantly higher in the $T = 1.6$ treatment as compared with either the $T = 2.8$ or $T = 3.5$ treatments ($p < .05$). Further, these same means are higher in the $T = 2.8$ treatment as compared with the $T = 3.5$ treatment. Importantly, Table 4 also indicates that initially, using means from just the first market of each session ("First market"), there are no differences in these three mean statistics across our three treatments, indicating that all sessions started out with roughly similar initial conditions and the choices of buyers and sellers then evolved over time to yield the differences summarized in Finding 1. The next three findings summarize aggregate behavior in each of the three experimental treatments.

Finding 2 *When $T = 1.6$, the experimental economies converge to (or nearly converge to) the all-payment-2 equilibrium.*

Support for Finding 2 comes from Table 2 and Figure 2a, which report on the evolution of behavior in the four sessions of the $T = 1.6$ treatment. In all four sessions, subjects move over time in the direction of the payment 2 equilibrium, which in this case represents a strict Pareto improvement for both sides. Furthermore, sellers do not suffer much loss from investing on the fixed cost: they can recover the fee if each buyer allocates just 4 EM (57%) or more to payment 2. As a result, sellers maintain high levels of acceptance, and this steadily high acceptance rate encourages buyers to quickly catch up, which, in turn, reinforces the incentives for acceptance of payment 2. As a result, toward the end of all four $T = 1.6$ treatment sessions, subjects have achieved convergence or near-convergence to the payment 2 equilibrium.

Finding 3 *When $T = 2.8$, there is a mixture of outcomes consistent with the greater multiplicity of equilibria in this treatment.*

Support for Finding 3 comes from Table 2 and Figure 2b, which report on the evolution of behavior in the four sessions of the $T = 2.8$ treatment. In contrast with the $T = 1.6$ treatment, the data reported in Table 2 and Figure 2b reveal a mixture of outcomes across the four sessions of the $T = 2.8$ treatment. In particular, we observe that the experimental economy either lingers in the middle ground between the all-payment-1 and all-payment-2 equilibria (sessions 1, 3 and 4) or appears to be very slowly converging toward the all-payment-2 equilibrium (session 2). Recall that when $T = 2.8,$ sellers are indifferent between the two equilibria as their payoffs are the same in either equilibrium. Further, any outcome where all buyers allocate the same proportion of their endowment to payment 2 as the fraction of sellers accepting payment 2 is always an asymmetric equilibrium in this setting. Generally we observe that the fraction of sellers accepting payment 2 hovers above (with some volatility) the fraction of endowment that buyers allocate to payment 2. If, over time, buyers increasingly insist on the new payment method 2, then sellers are likely to accommodate the buyers' choices by accepting it; this seems to be the case in session 2. In the final market of session 2, buyers' payment 2 allocation averages 96%, and six out of seven sellers (86%) accept payment 2. The number of payment 2 transactions increases from 55% in the first market to 84% in the last market. Note that compared with the $T = 1.6$ treatment sessions, the process of convergence to the all-payment-2 equilibrium is considerably slower, more erratic and incomplete. By contrast, in the other three sessions there is little to no evidence of convergence toward either the all-cash or all-e-money equilibrium. In session 3 there is a small increase in the number of transactions using payment 2 from 61% in the first market to 76% in the final market, but the economy remains far away from the all-payment-2 equilibrium, or any other symmetric equilibrium. In session 1, the number of sellers accepting payment 2 fluctuates between 2/7 (28.5%) and 5/7 (71.4%). Consequently, buyers are not willing to take the lead by acquiring high payment 2 balances, fearing that they will not be able to trade in case some sellers reject it. As a result, the buyer's average payment 2 allocation and the number of sellers accepting payment 2 both average between 40-50% throughout the entire session, but there is never coordination on the same rate. Finally, session 4 shows an upward trend in payment 2 usage in the first seven markets, but this trend abruptly halts thereafter, with the average number of payment 2 transactions barely changing from market eight onward (the value fluctuates between 67% and 71%). This outcome represents near (but imperfect) convergence to an interior equilibrium where approximately five out seven sellers are accepting payment 2 and buyers are allocating approximately 5 units of their 7 EM endowment to payment 2. This is the closest instance we have to a dual payments equilibrium outcome.

Finding 4 *When $T = 3.5$, the experimental economy slowly converges to the payment 1 equilibrium, or lingers in the middle ground between the two pure strategy equilibria.*

Support for Finding 4 comes from Table 2 and Figure 2c, which report on the evolution of behavior in the four sessions of the $T = 3.5$ treatment. When $T = 3.5$, sellers do better in the payment 1 equilibrium as compared with the payment 2 equilibrium; by contrast buyers always prefer the payment 2 equilibrium. Nevertheless, in each of the four sessions, more than 50% of sellers start out in the first market accepting payment 2, perhaps fearing that they will lose business in the case where some buyers show up with only payment 2 remaining. With experience, sellers learn to resist accepting payment 2 and engage in a tug of war with buyers; the average acceptance rate over all four sessions declines from 75% in the first market to just 21% in the last market. Sellers appear to be winning this contest in sessions 1, 2 and 4, pulling the economy back in the direction of the status quo, payment-1-only equilibrium. For example, in session 1, the buyer's payment 2 allocation falls from 65% in the first market to an average of just 6% in the last market. On the seller's side, six of seven (86%) of sellers accept payment 2 in the first market; by the end of the session, no seller is accepting payment 2. The number of payment 1 transactions increases from 35% in the first market to 94% by the final, 20th market; over the same interval, payment 2 transactions fall from 63% to 0%. In session 4, the trend works in favor of the seller, but the speed of convergence is very slow; at the end of the session, two sellers (29%) continue to accept payment 2 and 22% of transactions are conducted in payment 2 (however, it seems reasonable to conjecture that the economy would get even closer to the payment 1 equilibrium if the session lasted more than 20 markets). In session 3, the tug of war continues throughout the session and neither side is able to gain the upper hand; in that session, the average buyer's payment 2 allocation and the number of sellers accepting payment 2 consistently fluctuates around 50%, but there is no coordination on any asymmetric equilibrium in this setting.

An immediate implication of Findings 1 to 4 is the following:

Finding 5 *Efficiency losses increase with increases in T.*

Support for Finding 5 comes from Table 3. When $T = 1.6$, the economy quickly converges to the socially efficient payment 2 equilibrium. All four sessions achieve between 92% and 96% of the socially optimal (payment-2-only) equilibrium payoffs, with the overall average being 94%. The efficiency measure falls as T increases to 2.8, ranging from 75% to 85%, with a treatment average of 81%. Treatment $T = 3.5$ induces a further decrease in the efficiency measure, with efficiency measures ranging from 72% to 75% and a treatment average of 75%. As the fixed cost increases, the economy moves further away from the efficient equilibrium. At the same time, mis-coordination in payment choices becomes more severe, as manifested in the increasing frequency of no-trade meetings, which averaged 0.8% for $T = 1.6$, 5.6% for $T = 2.8$ and 8.6% for $T = 3.5$.

The picture is unchanged if we consider earnings relative to the status quo where only payment 1 is used. The percentage of subjects' earnings relative to the payment 1 equilibrium level serves as a measure of the benefit of introducing the new payment method, payment 2.[13] As revealed in the bottom half of Table 3, there are significant positive welfare benefits to the introduction of payment 2 when $T = 1.6$, moderate benefits when $T = 2.8$, but almost no benefit when $T = 3.5$. Disaggregating by role, Table 3 further reveals that in all three treatments buyers benefit relative to the payment 1 equilibrium, while sellers only benefit in the $T = 1.6$ treatment and sellers suffer in the other two treatments relative to the payment 1 equilibrium benchmark. The latter finding is summarized as follows.

Finding 6 *Sellers may choose to accept the new payment method (payment 2) even if doing so reduces their payoffs relative to the status quo where only payment 1 is used.*

Merchants often complain about high costs associated with accepting electronic payments but feel obliged to accept those costly payments for fear of upsetting or losing their customers (the so-called "must-take" phenomenon). A recent study by Bounie, François and Van Hove (2017) finds that in the case of France in 2008, the must-take phenomenon applies to 5.8-19.8% of card-accepting merchants.[14] We observe a similar pattern in our experiment. For instance, when $T = 3.5$, although sellers understand that they will lose relative to the status

[13]Since payment 1, representing cash, has to be accepted by legal restriction, it is natural to think of payment 2 as the new and competing payment method.

[14]Some evidence in support of this claim comes from Evans (2011, p. vi), who observes that "...the US Congress passed legislation in 2010 that required the Federal Reserve Board to regulate debit card interchange fees; the Reserve Bank of Australia decided to regulate credit card interchange fees in 2002 after concluding that a market failure had resulted in merchants paying fees that were too high; and in 2007 the European Commission ruled that MasterCard's interchange fees violated the EU's antitrust laws."

quo if the economy moves to the payment 2 equilibrium, most sellers still begin the session accepting the new payment method (the average frequency of sellers accepting payment 2 in the first market is 70% in treatment $T = 2.8$ and 76% treatment $T = 3.5$). Furthermore, in all sessions with $T = 2.8$ and 3.5, throughout all 20 markets, the seller's average payoff is always below 3.5, the payoff that they would earn were the economy staying in the payment 1 equilibrium.[15]

5 Individual Experimental Results

In this section we explore in further detail individual decision-making in our experiment. In particular, we first examine how the portfolio decisions of buyers depend on past market outcomes and their beliefs for the current market. We then do the same for sellers' decisions to accept or not accept payment 2.

Table 5 reports regression estimates from a linear, random-effects model of the buyer's payment 2 allocation choice (card choice) where the random effect is at the individual buyer level. Specifically, the dependent variable is the percentage of the buyer's endowment that he/she allocated to payment 2 (card choice %). The two main explanatory variables are mktAcceptL(%), representing the percentage of sellers accepting payment 2 in the last market, and bBelief%, the buyer's own incentivized belief as to the number of sellers who would be accepting payment 2 in the current market.[16] Additional explanatory variables are the market number, 1,2...20 ("market") to capture learning effects, a location dummy ("location") equal to 1 if the data were collected at SFU and two further treatment dummies, $T16$ and $T35$, to pick up treatment level effects from the $T = 1.6$ and $T = 3.5$ treatments respectively (the baseline treatment is thus $T = 2.8$).

The first column of Table 5 reports results using the pooled data from the entire experiment using all six of these explanatory variables. The results indicate that all variables except the location dummy are statistically significant; the latter finding tells us that on the buyer side there was no significant difference in buyer behavior between SFU and UCI and thus rationalizes our pooling of the data from these two populations. We note that among the statistically significant explanatory variables, all but the coefficient on the T35 dummy variable have positive coefficients.

[15] See Figures Ab and Ac in Appendix A.

[16] Buyers learned the percentage of sellers accepting payment 2 in the prior market because they visited all seven sellers and were informed in every instance whether or not the seller accepted payment 2. In addition, we reported information on the percentage of sellers who accepted payment 2 in all prior markets on buyers' stage 1 portfolio allocation screen. Thus buyers had ready access to the statistic mktAcceptL.

The interpretation of these results is straightforward. Buyers increase their allocation to payment 2 when: the past market seller acceptance of payment 2 is greater; buyers believe that more sellers will accept payment 2 in the current market; the market number is higher; and $T = 1.6$. If $T = 3.5$, there is a significant drop in buyers' allocations to payment 2, as buyers anticipate the consequences of higher seller fixed costs for seller acceptance of payment 2. The last three columns of Table 5 report on the same regression model specifications but using the data separately from each of the three treatments (thus omitting the T16 and T35 dummies). As these last three columns reveal, buyers' allocation of their endowment to payment 2 is again increasing in both the past market percentage of sellers accepting payment 2 and in buyers' beliefs about the percentage of sellers who will accept of payment 2 in the current market. However, the coefficient on the market variable ranges from a positive and significant 0.699 when $T = 1.6$ to 0.197 when $T = 2.8$ to a negative and significant -0.404 when $T = 3.5$, which indicates that buyer behavior is consistent with Finding 1. Notice further that the location dummy variable is significantly positive for $T = 1.6$ and $T = 2.8$ treatments, but negative in the $T = 3.5$ treatment, which indicates that while there were differences in individual buyer behavior across the two locations at the treatment level, overall, across all three treatments there is no systematic bias (all positive or all negative) in buyers' allocations of endowment to payment 2 (as confirmed again by the insignificance of the location dummy using the pooled data). We summarize these results as follows.

Finding 7 *Buyers' allocations to payment 2 depend on historic market outcomes, their current beliefs about seller acceptance of payment 2 and the value of* T.

As each seller's decision to accept payment 2 or not is a binary choice, Table 6 reports on a random effects probit regression analysis of the factors affecting individual sellers' payment 2 acceptance decisions where the random effect is at the individual seller level. For the pooled data analysis from all three treatments (the first column of Table 6), we consider nine explanatory variables, the last four of which are the same ones that were used in the regression analysis reported in Table 5. The five other explanatory variables are as follows: sOtherAcceptL(%), which is the percentage of sellers who accepted payment 2 in the previous market (this information was only revealed to sellers at the start of stage 1 of each new market when they had to make a payment 2 acceptance choice and *not* earlier); sAcceptL*sCardDealL(%), which is the percentage of transactions the seller succeeded in conducting using payment 2 in the previous market conditional on his having accepted payment 2 in that previous market, i.e., if sAcceptL=1; (1-sAcceptL)*sNoDealL(%) is the percentage of no trade outcomes the seller encountered in the previous market conditional on his/her having refused to accept payment 2 in that previous market, i.e., if sAcceptL=0; and sBeliefB and sBeliefS, which are the seller's incentivized beliefs about the buyers' average allocation of endowment to payment 2 and of the percentage of the other six sellers (excluding themselves) who would accept payment 2, respectively, in the current market.

Table 6 reports marginal effects of these explanatory variables on the seller's probability of accepting payment 2. For the pooled data estimates (first column of Table 6), we observe that the percentage of other sellers accepting payment 2 in the prior market has no statistically significant effect on a seller's current market decision to accept payment 2. However, sellers do respond to their *own* prior market experience from accepting or not accepting payment 2. In particular, sellers who accepted payment 2 in the prior market are more likely to accept it again, the higher the percentage of transactions they completed using payment 2 in that prior market. Sellers who did not accept payment 2 in the prior market are more likely to accept it in the current market, the larger the number of no trade transactions they experienced in that prior market.[17] The disaggregated treatment-level regression estimates reported on in the last three columns of Table 6 reveal that these latter two effects are coming mainly from the $T = 3.5$ treatment. In that treatment, sellers face the highest fixed cost for adopting payment 2 and as a result they pay more careful attention to the payoff consequences of prior payment 2 acceptance or non-acceptance decisions in this treatment relative to the other two, where the fixed costs of accepting payment 2 were lower. We further observe that sellers' willingness to accept payment 2 is positively affected by their beliefs about the percentage of buyers' endowment that would be allocated to payment 2 in the current market and by their beliefs about the percentage of other sellers who would accept payment 2 in the current market. The latter finding holds both for the pooled data and for the individual treatment specifications. The market variable is not statistically significant in the pooled seller regression, though it is negative and significant for the $T = 2.8$ treatment alone; sellers in that treatment were more likely to accept payment 2 with experience. There is again an absence of any location effect on the seller side as evidenced by the insignificant estimate on the location dummy variable both in the pooled data and in the individual treatment specifications. However, there is again a strong treatment effect as indicated by the positive and negative coefficients on the T16 and T35 dummies, respectively; sellers in the $T = 1.6$ treatment were more likely to accept payment 2 while those in the $T = 3.5$ treatment were more likely to reject payment 2, all relative to the $T = 2.8$ treatment baseline. We summarize our findings for seller behavior as follows:

Finding 8 *Sellers' acceptance of payment 2 depends on historic market outcomes, their current beliefs about buyer allocations to payment 2, other sellers' acceptance of payment 2 and*

[17] A no-trade outcome can only occur in the case where the seller does not accept payment 2 and the buyer has only payment 2 in his/her portfolio. Sellers must always accept payment 1 (cash).

the value of T.

Summarizing the regression results, we have found that past market outcomes and beliefs matter for both buyer and seller behavior in a manner that is consistent with our theory. Buyers pay attention to the prior distribution of sellers accepting payment 2 when making portfolio allocations and sellers condition their payment 2 acceptance decisions on their own prior experiences with accepting or not accepting payment 2. Buyers act on their beliefs about the current distribution of sellers accepting payment 2 and sellers act on their beliefs about the current percentage of payment 2 held by buyers and on the current decisions of other sellers to accept payment 2. We have also confirmed the strong treatment effects we report on earlier in finding 1. Finally, we have not found evidence for any strong location effects in the decisions made by buyers or sellers, despite the fact that we conducted our experiment using student subjects at two different universities, SFU and UCI.

Findings 7 and 8 suggest that the payment choice in our experiment exhibits a strong network effect, evidenced by the strong response of buyers' portfolio choices to the seller's acceptance decision in the past and buyers' beliefs about sellers' choices in the coming market. Similarly, sellers' acceptance decisions are affected by their past trading experiences with buyers and their beliefs about buyers' portfolio decisions in the coming market. Such data are not available for many empirical studies on network externalities and certain techniques have been developed to test the network effect indirectly. One such technique is to estimate the two sides' decisions jointly and test the network externality by testing if the correlations of the residuals from the regressions on the two sides are nonzero. It is an interesting exercise to validate the estimation strategy with our experimental data. To do this, we re-did the analysis of Tables 5 and 6 using a conditional mixed process estimator where the specifications of Tables 5 and 6 are jointly estimated (column 1). In addition, we considered specifications where we exclude the lagged market acceptance decisions (column 2), elicited beliefs (columns 3) and both (column 4). The results from this conditional mixed effects estimation are reported in Table A1 in Appendix A. We observe that the correlation between the residuals from the buyer and seller regression models is only significant in specification (4). In particular, for the full specification, the cross-equation correlation of the errors is not significantly different from zero. The results from the conditional mixed process estimate suggests that the technique developed for filed data is indeed valid.

We can also use our experimental data to investigate whether the network externality can be a source of state dependence and use the result to inform empirical studies with field data. Tables A2 and A3 in Appendix A report on whether there is state dependence in buyer and seller payment choices, respectively, by adding the lagged payment choice as an explanatory variable.[18] In Table A2 we observe that the lagged buyer choice term is statistically significant in all four regressions, but the magnitude of the coefficient decreases significantly when the last market and belief terms (especially the belief term) are added. Table A3 checks state dependence for seller choice. The lagged seller choice term is statistically significant in specifications (1) to (3), but becomes insignificant in regression (4) when both market and belief terms are added. The value of the coefficient also decreases significantly. The results from these regressions suggest that the network externality could be a source of state dependence. Empirical works that do not account for the network externality may generate spuriously high state dependence. A recent study by Huynh et al. (2017) on the adoption of ATM cards in Italy focuses only on consumer adoption and generates a large fixed cost of about 14,000 euros. Part of this fixed cost could be due to network externalities.

6 An Evolutionary Learning Model of Payment Choice

While our theoretical model is static, the adoption of a payment method is inherently a dynamic process. Our experiment suggests that this dynamic process involves some learning over the repeated markets of our design. Toward a better understanding of this dynamic learning process, in this section we present an evolutionary learning model approach to payment choice and compare simulation results using that model with our experimental data. After establishing that our evolutionary model provides a good fit to our experimental data, we use the model to predict outcomes for a fourth experimental treatment. That is, we use the evolutionary model for experimental design. We then carried out the additional experimental treatment and again found a good fit between the evolutionary model and the experimental data.

6.1 The IEL Model

The evolutionary learning model we use is the individual evolutionary model (IEL). The model has been successfully used to characterize and predict the behavior of human subjects in many different economic environments (see, for example, Arifovic and Ledyard, 2007, 2011, 2012, 2017; Arifovic, Boitnott and Duffy, 2016).

In this model, each individual agent is endowed with a set of J strategies. This collection of strategies is updated each period based on evaluation of agent i's *foregone* payoff from

[18] For these regressions, we did not use a random effects estimator since adding the lagged term means that the random effect term becomes correlated with other explanatory variables (i.e., the lagged term), and this makes the estimation inconsistent.

using each strategy, i.e., how each strategy would have performed had it been used in that period. Strategies with higher foregone payoffs increase the frequency of their representation in each agent's strategy set. Finally, there is a probability of experimentation, which brings new strategies into the set. The strategy that is actually used by each agent in a given period is selected randomly, where the probability of selection is proportional to a strategy's relative foregone payoff among the strategies in the agent's set.

The environment in which we simulate the IEL model corresponds to our experimental environment, i.e., it is inhabited by seven buyers and seven sellers, and it lasts for 20 markets (periods) with each period involving a first payment choice stage followed by a second stage of seven trading rounds. The sequence of events in each period and round exactly follows the experimental design. The artificial agents have the same amount of information that the human subjects had at every decision node.

Each of the seven artificial buyers and sellers in our evolutionary model has as a set of J rules; each rule consists of a single number. For buyer $i \in \{1, 2, ..., 7\}$, a rule $m^i_{b,j}(t) \in \{0, 1, ..., 7\}$, where $j \in \{1, 2, ..., J\}$, represents the number of EM units the buyer places in payment 2 in market t.[19] For seller $i \in \{1, 2, ..., 7\}$, a rule $m^i_{s,j}(t) \in [0, 1]$, where $j \in \{1, 2, ..., J\}$, represents the probability that the seller accepts payment 2. When a particular seller rule is selected as an actual rule, a random number between 0 and 1 is drawn from a uniform distribution over $[0, 1]$. If that number is less than or equal to $m^i_{s,j}(t)$, the seller decides to accept payment 2. Otherwise, the seller decides not to accept payment 2 for that market.

The initial set of J rules (strategies) for all buyers and sellers is randomly chosen. The one strategy chosen for each buyer and seller for the initial market from their initial set of J strategies is also randomly chosen. The updating of the buyers' and sellers' sets of rules takes place at the end of each seven-round market and consists of four steps:

1. Experimentation. Experimentation introduces new, alternative rules that otherwise might never have a chance to be tried. It ensures that a certain amount of diversity is maintained. This operation involves changing each element of the current set of rules to a new rule with some probability, μ. The new rule is drawn from a normal distribution, with mean equal to the current rule and standard deviation equal to 10% of the size of the choice set (i.e., 0.7 for buyers and 0.1 for sellers).[20]

[19] To be precise, the buyer's rule is a real number between 0 and 7, which is rounded to the nearest integer if the rule is selected.

[20] If the draw from the normal distribution is larger (smaller) than the upper (lower) limit of the choice set, then it is truncated to the upper (lower) limit of the choice set.

2. Foregone payoff calculation. As the rules that our IEL sellers and buyers use are simple, the foregone payoff calculation is what gives the algorithm its power. The foregone payoff calculation depends on whether an agent is a buyer or a seller.

   At the end of each period, buyers know the number of sellers who actually accepted payment 2 in that period, $s_a(t) \in \{0, 1, ..., 7\}$. For buyers, the foregone payoff of each rule $m^i_{b,j}(t)$ in buyer i's set at the end of market t is computed in the following way.

$$\Pi^i_{b,j}(t) = (7 - m^i_{b,j}(t))(u - \tau) + \min\left[s_a(t), m^i_{b,j}(t)\right](u - \tau^e).$$

   Note that in our simulation, we assume that the buyer adopts the following (payoff-maximizing) strategy (given his initial payment allocation): if the buyer meets a seller who accepts payment 2, then the buyer uses payment 2 if he still has payment 2 left and he uses payment 1 otherwise; if the seller does not accept payment 2, then the buyer uses payment 1 if he still has some payment 1 left and he does not trade otherwise. Note that if $m^i_{b,j}(t)$ is larger than $s_a(t)$, then $s_a(t)$ is used in the calculation and there is missing trade in some rounds, where the buyer has only payment 2 left and the seller does not accept it.

   The computation of sellers' foregone payoffs is more complex. For each seller, we use two variables to compute the foregone payoffs of all the rules in a seller's set. The first variable is $s^{-i}_a(t) \in \{0, 1, ..., 6\}$, the number of sellers excluding seller i that accepted payment 2. Recall that this information was provided to sellers at the end of each market of the experiment. The second variable is $s^f\bar{m}^i_b(t) \in \{0, 1, ..., 7\}$, the forecast of seller i of the average allocation to payment 2 by all 7 buyers. Note that in our experiment buyers' allocations to payment 2 are not public knowledge, but we did elicit sellers' forecasts of buyers' average allocation to payment 2. Thus, our artificial agents, like the human subjects, must form an expectation of this value. The updating of this expectation is seller-specific and depends on each seller's experience from the previous period; the details of this updating are given in Appendix B. After we have $s^{-i}_a(t)$ and $s^f\bar{m}^i_b(t)$, we use them to evaluate foregone payoffs for all of the rules in a seller's rule set in three steps.

   First, we calculate the expected number of transactions that would have been completed using payment 2 provided that the seller had accepted payment 2:

$$n^{i,a}(t) = 7 * \min\left[s^f\bar{m}^i_b(t)/(s^{-i}_a(t) + 1), 1\right], \tag{1}$$

   and the expected profit from doing so (note that $7 - n^{i,a}(t)$ transactions use payment

1):

$$\pi_s^{i,a} = n^{i,a}(t)(u - \tau^e) + (7 - n^{i,a}(t))(u - \tau) - F. \tag{2}$$

Second, we calculate the expected number of transactions involving payment 1 that would have taken place if the seller did not accept payment 2:

$$n^{i,n}(t) = 7 * \min\{1, (7 - s^f \bar{m}_b^i(t))/(7 - s_a^{-i}(t)), \tag{3}$$

and the expected payoff from doing so (note that transactions can only be carried out with payment 1):

$$\pi_s^{i,n}(t) = n^{i,n}(t)(1 - \tau). \tag{4}$$

Finally, for each rule j that is in seller i's rule set, we calculate the expected foregone payoff as the weighted average of $\pi_s^{i,a}(t)$ and $\pi_s^{i,n}(t)$:

$$\Pi_{s,j}^i(t) = m_{s,j}^i(t)\pi_s^{i,a}(t) + (1 - m_{s,j}^i(t))\pi_s^{i,n}(t). \tag{5}$$

3. Replication follows experimentation. Replication reinforces rules that would have been good choices in previous periods. Specifically, rules with higher foregone payoffs are more likely to replace those with lower foregone payoffs. We implement replication using the following tournament process: we randomly pick two members of the current set of J rules with replacement, compare their forgone payoffs, and place the rule with the higher payoff in the new set of rules; we repeat this process J times so that the new set of rules has J members.

4. Selection. We randomly choose one rule from the set of J rules based on foregone payoffs; the probability with which a strategy is selected is proportional to its relative foregone payoff among the player's set of rules.

6.2 Simulation Results and Comparison with the Experimental Data

After our first three treatments, we adapted the IEL model in the manner described above, to capture the dynamics of our experimental data. Note that the IEL has only two free parameters: the size of the individual strategy set, J, and the experimentation rate, μ. In our simulations, we set $\mu = 0.133$ and $J = 150$.[21] With these choices we found that the IEL model captured the experimental data quite well. Figures 3a, 3b and 3c show the evolution

[21] We did some robustness checks for these two parameters and found that the algorithm continues to characterize the experimental data well so long as $\mu > 0.10$ and $J \geq 50$.

of the payment choice in four selected simulation sessions alongside the experimental sessions for $T = 1.6$, 2.8 and 3.5, respectively. The IEL model is able to generate paths very similar to those of the experimental sessions. In particular, for $T = 1.6$, there is quick convergence to the all-payment-2 equilibrium. For $T = 2.8$, there is a mixture of outcomes: the simulated economies can either linger in the middle ground between the all-payment-1 or all-payment-2 equilibria, or slowly converge to the all-payment-2 equilibrium. For $T = 3.5$, the simulated sessions either slowly converge to the all-payment-1 equilibrium or linger in the middle ground between the two pure strategy equilibria. In Figure 4, we graph the path of the payment choice averaged across the four experimental sessions and the four simulated sessions; again the simulated path exhibits a pattern similar to that of the experimental sessions (the lowest panel graphs the path of the payment choice averaged across 50 simulated sessions, which is smoother because of the large number of simulations).

Encouraged by the good fit between the experimental and IEL model simulations for the first three treatments, we used the IEL algorithm to run simulations with higher values of T. We were particularly interested in understanding how large T needed to be in order for there to be coordination on the all-cash equilibrium, subject to the constraint that the all e-money equilibrium remained the socially efficient equilibrium (i.e., $T < 5.6$). We find that the simulated economies almost always converge to the all-payment-2 equilibrium within 20 markets for $T = 4.0$ and higher. To further validate the IEL model's characterization of our experimental data, we ran a new experimental treatment with $T = 4.5$ to confirm this prediction.

As predicted by the IEL model, all four experimental sessions converge very close to the all-payment-2 equilibrium by the end of the experiment (see Figure 2d, which graphs the time path of payment choice and usage; Figure 3d, which compares the time path of payment choice of the experimental and selected simulated sessions; and the last column of Figure 4, which compares the time path of payment choices averaged across the experimental sessions and across the simulated sessions).

In summary, the IEL algorithm provides a dynamic model of behavior that seems to approximate the dynamic path taken by the subjects in the experiment very well.

6.3 Analysis of the New Treatment

In this subsection we briefly analyze the experimental data from the new treatment (more details are provided in Figures 2d, and Tables 7 to 10).

The experimental sessions converge very close to the all-payment-1 (all cash) equilibrium. Averaged across the four sessions, by the end of the last market, buyers allocate 93% of their money to payment 1; 14% of sellers (1 out of 7) choose to accept payment 2; and 93% of transactions are conducted with payment 1 (see Table 7). Compared with the other three treatments, payment mismatch is more serious: averaged across the 20 markets and the four sessions, 12% of meetings result in no trade, versus 9% for $T = 3.5$, 6% for $T = 2.8$ and 1% for $T = 1.6$. As a result, there is higher efficiency loss (see Table 8). Averaged across the 20 markets and the four sessions, the experimental economies achieve 87% of the payoff were the economy staying in the all-payment-1 equilibrium; the corresponding number is 98% for $T = 3.5$, 114% for $T = 2.8$ and 148% for $T = 1.6$.

The regression for the buyer's payment choice (see Table 9) suggests that buyers respond strongly to their beliefs on the seller's acceptance decision: the coefficient on the term bBelief is 0.767, meaning that a 1% increase in this belief induces 0.767% increase in payment 2 allocation. Across time, buyers reduce their allocation to payment 2: the coefficient on the market number variable is -0.619 (from market 1 to 20, the reduction is about 12%). Subjects at SFU tend to allocate more to payment 2. The coefficient on the location dummy is marginally significant at the 10% significance level, but the magnitude is small at less than 4%.

The regression for the seller's acceptance decision (see Table 10) suggests that sellers respond to historic market outcomes, their current beliefs about buyer allocations to payment 2, and other sellers' acceptance of payment 2.

In general, similar to the first three treatments, the regression results for the new treatment suggest a strong network effect: subjects respond to their beliefs about the other side of the payment system and past outcomes.

7 Conclusion and Directions for Future Work

We have developed a simple model to understand factors that may contribute to the adoption of a new payment method when there already exists a payment method that all sellers accept. Specifically, we have isolated two factors: network adoption effects and seller transaction costs as determinants of whether or not the new payment method can take the place of the existing payment system. As our model admits multiple equilibria for a wide set of parameter values, we have chosen to study the behavior of human subjects placed in a simple version of that model, incentivize them to make decisions in accordance with the theory, and give them ample opportunities to learn how to make choices in that environment.

Our model/experiment involves a two-stage game. In the first stage, sellers decide whether or not to accept the new payment method; they must always continue to accept the old payment method. Simultaneously in this first stage, buyers decide how to allocate their endowment between the two payment methods without knowing of seller acceptance decisions. To use the new payment method, the seller has to pay a fixed cost to accept it, but the new payment method saves on per transaction costs for both buyers and sellers. As a result of the network effect, the status quo where the existing payment is used and complete adoption of the new payment method are both equilibria.

Our main treatment variable is the fixed cost to accept the new payment method. We find that the new payment method will take off if the fixed cost is low so that both sides benefit by switching to the new payment method. If the fixed cost is high such that the seller endures a loss in the equilibrium where the new payment method is used relative to the equilibrium where it is not accepted, some sellers nevertheless respond by accepting the new payment method initially, fearing to lose business, but they mostly eventually learn over time to resist the new payment method and pull the economy back to the old payment method. If neither side displays much willpower to move behavior toward one equilibrium or the other, then the economy may linger in the middle ground between the two equilibria.

We also find that an evolutionary learning model captures the dynamic process of payment choices well. The simulation results from the learning model provide a good fit to our experimental data, and the learning model is useful for the design of new treatments.

The framework we have developed in this paper can be used to analyze a series of new questions. (1) What are the effects of subsidies and taxes on the adoption of a new payment method? Consider schemes with balanced budgets where subsidies are financed by taxes. Which schemes are more effective in promoting the new payment method: charging sellers to subsidize buyers or the other way around? (2) In the baseline model, we fix the terms of trade. What will happen if we allow sellers to offer discounts or impose surcharges (i.e., pass-throughs)? Will sellers use discounts or surcharges? How will discounts or surcharges affect the diffusion of the new payment method? (3) The baseline model assumes a single new payment method. It is of interest to further explore how the economy evolves if there is more than one new payment method. Imagine the simplest case featuring two new payment methods with the same setup cost. Because of the positive setup cost associated with each new payment method, the most efficient allocation is to use only one new method. Competition between the two new payment methods may make it difficult for agents to coordinate on a single new payment method. As a result, it is possible that neither payment method will take off, or it may take a longer time for the economy to converge to the efficient equilibria. (4) What are the desirable features of the existing payment method, i.e., cash, that the new payment method needs to retain in order to make it more competitive? Anonymity? Robustness to network breakdowns? What is the effect of an incidence of identity theft? Suppose the economy has arrived at the equilibrium with the new payment method. Can the economy revert to the cash-only equilibrium, and if so, under what circumstances? (5) Suppose consumers receive their income in the form of either the old or the new payment method and assume there is a small cost of portfolio adjustment at the beginning of each trading period. Do these changes matter for the equilibrium that is selected? (6) The baseline model assumes that sellers always accept the old payment method. What would happen if we relax this assumption and allow sellers to decide whether to accept the old payment method? (7) The baseline model assumes that consumers cannot convert between the old and the new payment methods after the initial portfolio choice. As a result, if the consumer has only the new payment method but the seller does not accept it, there will be no trade. In such instances, we could modify the model to allow for conversion opportunities subject to a cost. Note that this new specification does not change the equilibrium outcomes. In equilibrium, consumers' portfolio choice will be fully consistent with the seller's acceptance pattern, and there is no need to convert. However, the conversion cost(s) may affect the speed of convergence to equilibria. We believe that all of these extensions of our model are worth examining theoretically and/or experimentally, but we must leave such an analysis to future research.

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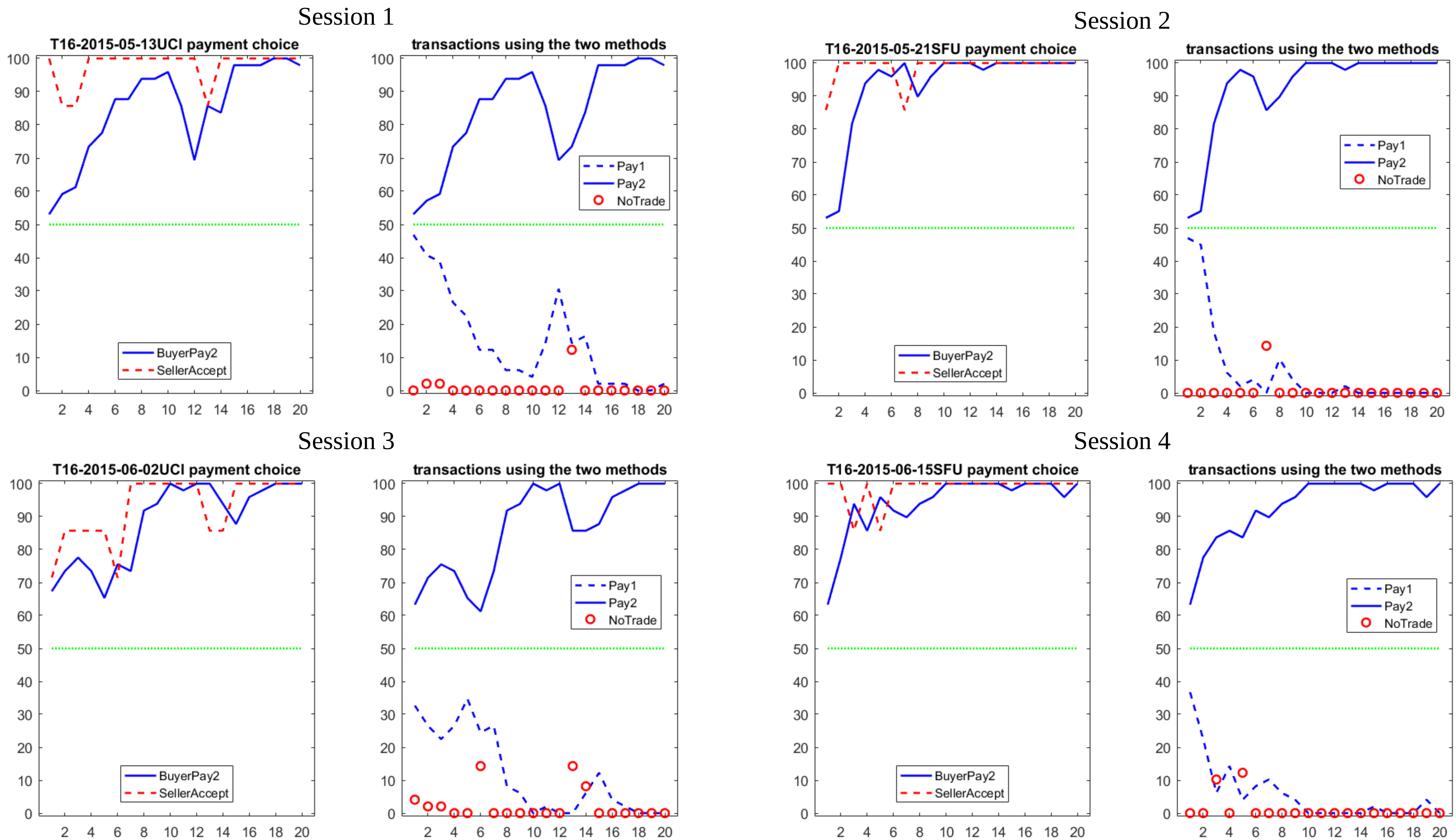
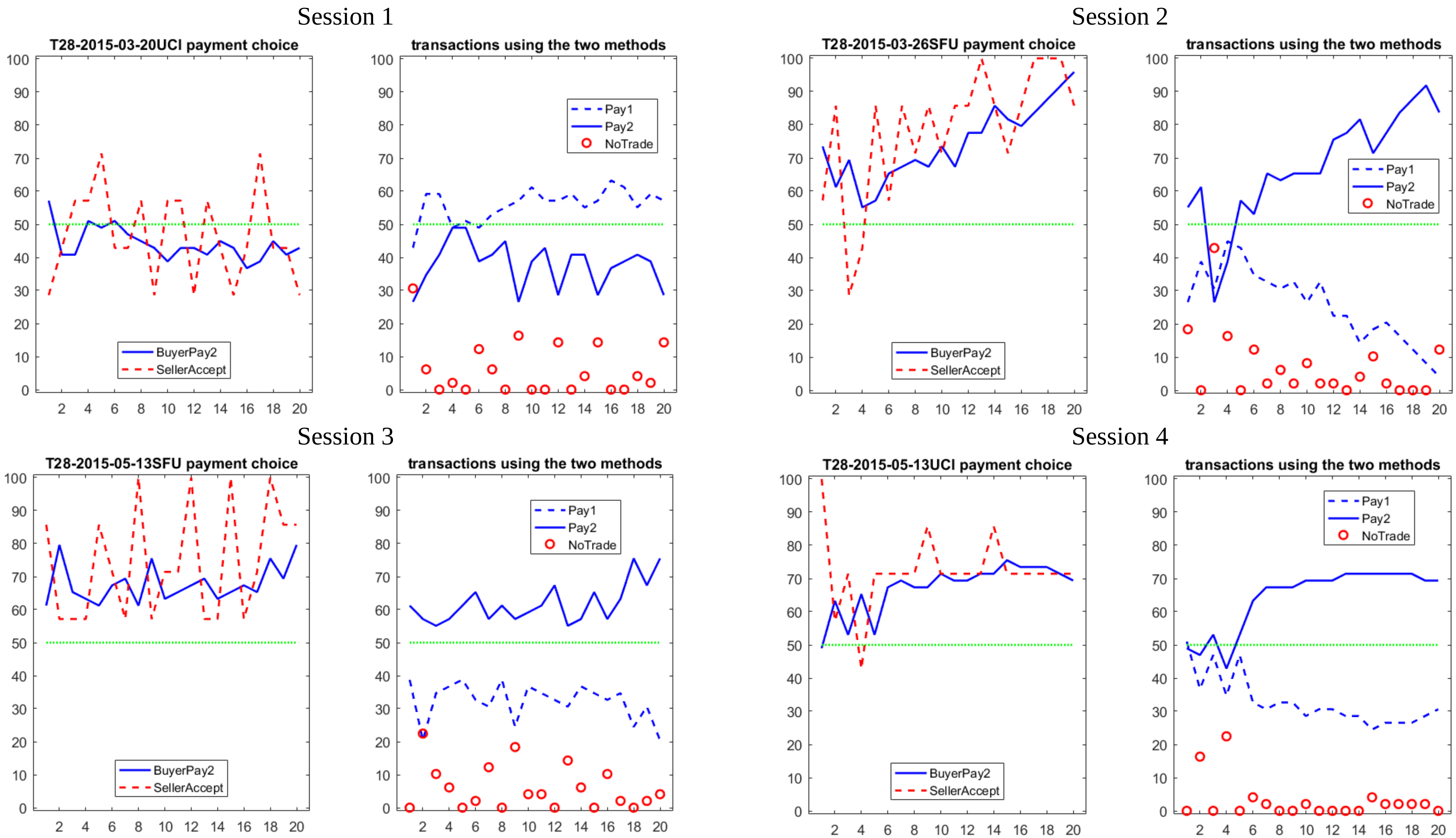
Figure 2a: Payment Choice and Usage T=1.6



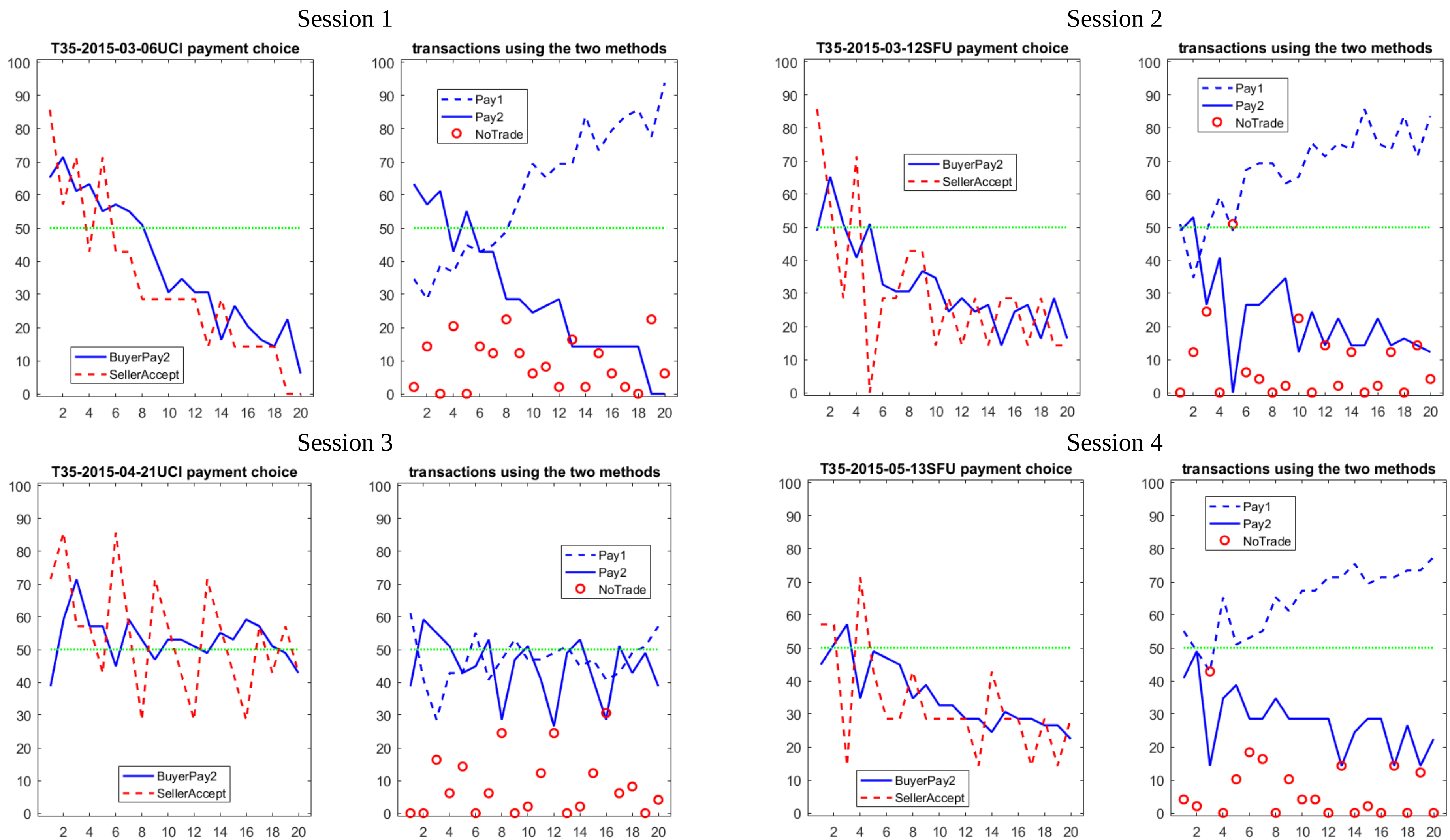
Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first shows payment choices: the red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2. The second figure describes payment usage. The solid blue line is the percentage of meetings using payment 2; the dashed blue line is the percentage of meetings using payment 1; red circles are the percentage of meetings where no trade takes place.

Figure 2b: Payment Choice and Usage T=2.8



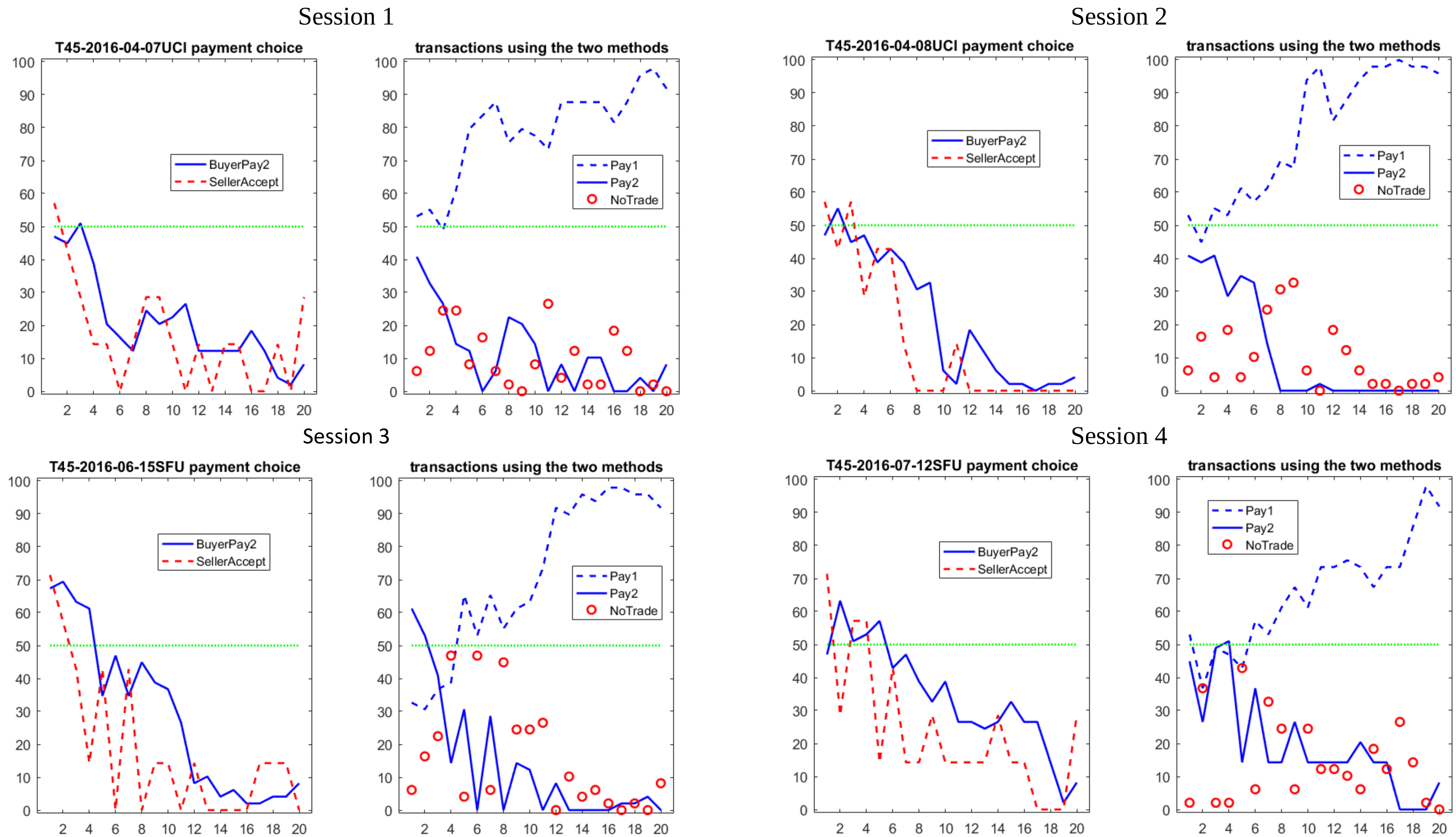
Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first shows payment choices: the red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2. The second figure describes payment usage. The solid blue line is the percentage of meetings using payment 2; the dashed blue line is the percentage of meetings using payment 1; red circles are the percentage of meetings where no trade takes place.

Figure 2c: Payment Choice and Usage T=3.5



Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first shows payment choices: the red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2. The second figure describes payment usage. The solid blue line is the percentage of meetings using payment 2; the dashed blue line is the percentage of meetings using payment 1; red circles are the percentage of meetings where no trade takes place.

Figure 2d: Payment Choice and Usage T=4.5



Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first shows payment choices: the red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2. The second figure describes payment usage. The solid blue line is the percentage of meetings using payment 2; the dashed blue line is the percentage of meetings using payment 1; red circles are the percentage of meetings where no trade takes place.

Figure 3a: Payment Choice in Sample Simulated Sessions T=1.6

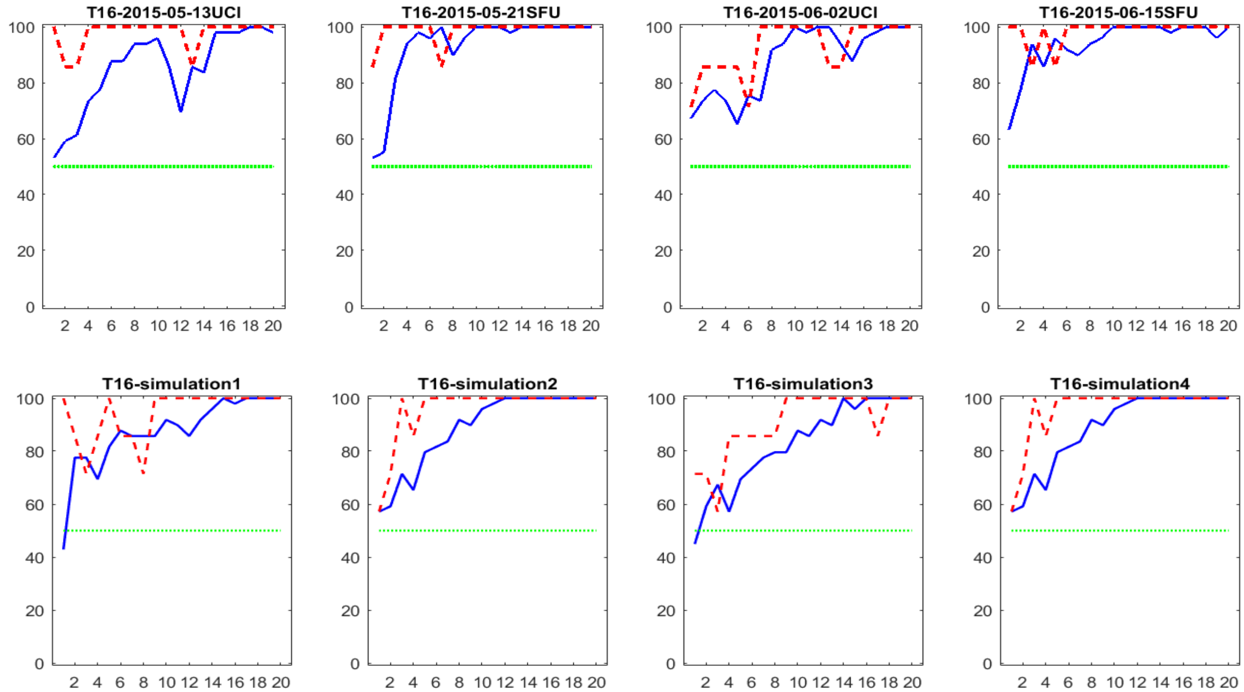
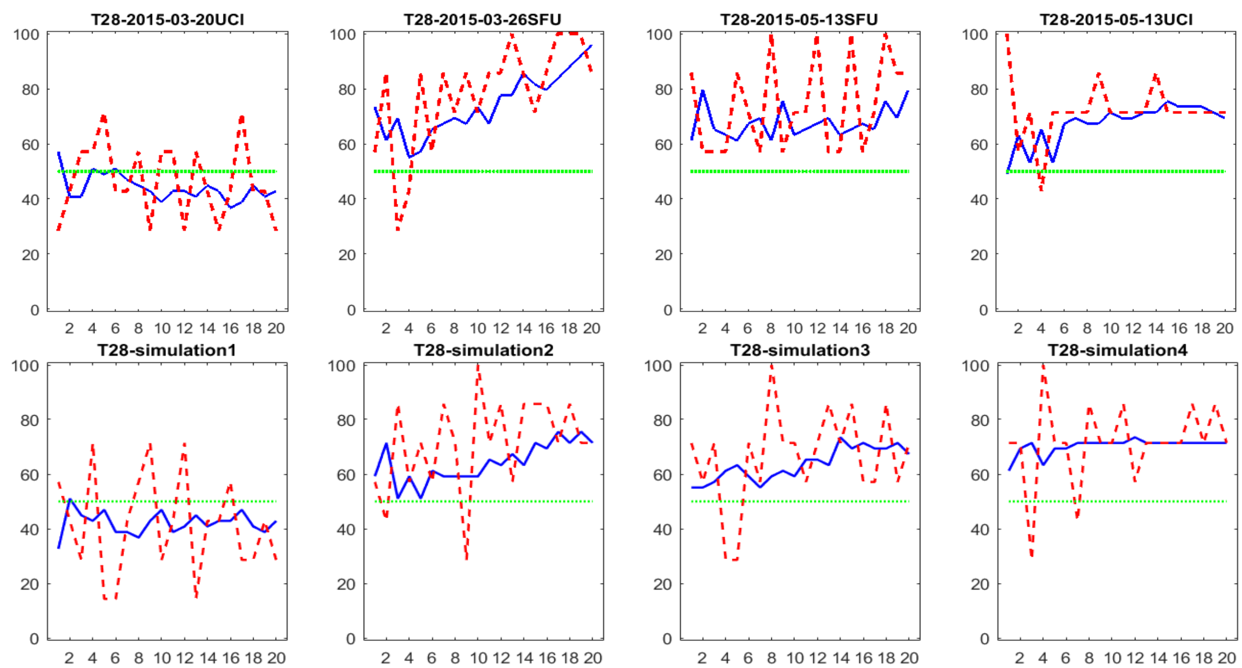


Figure 3b: Payment Choice in Sample Simulated Sessions T=2.8



Notes. (1) The 4 figures in the first row represent the 4 experimental sessions for reference, and the 4 figures in the second row represent sample simulated sessions under the IEL. (2) Horizontal axis: market. (3) The red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2.

Figure 3c: Payment Choice in Sample Simulated Sessions T=3.5

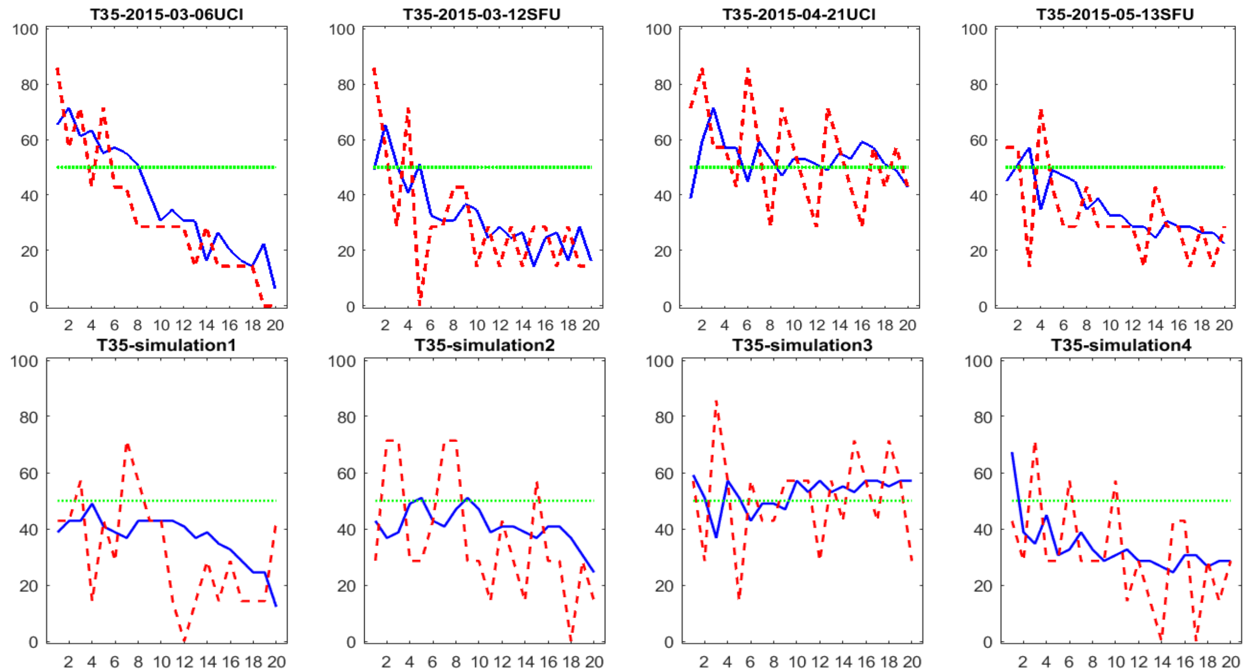
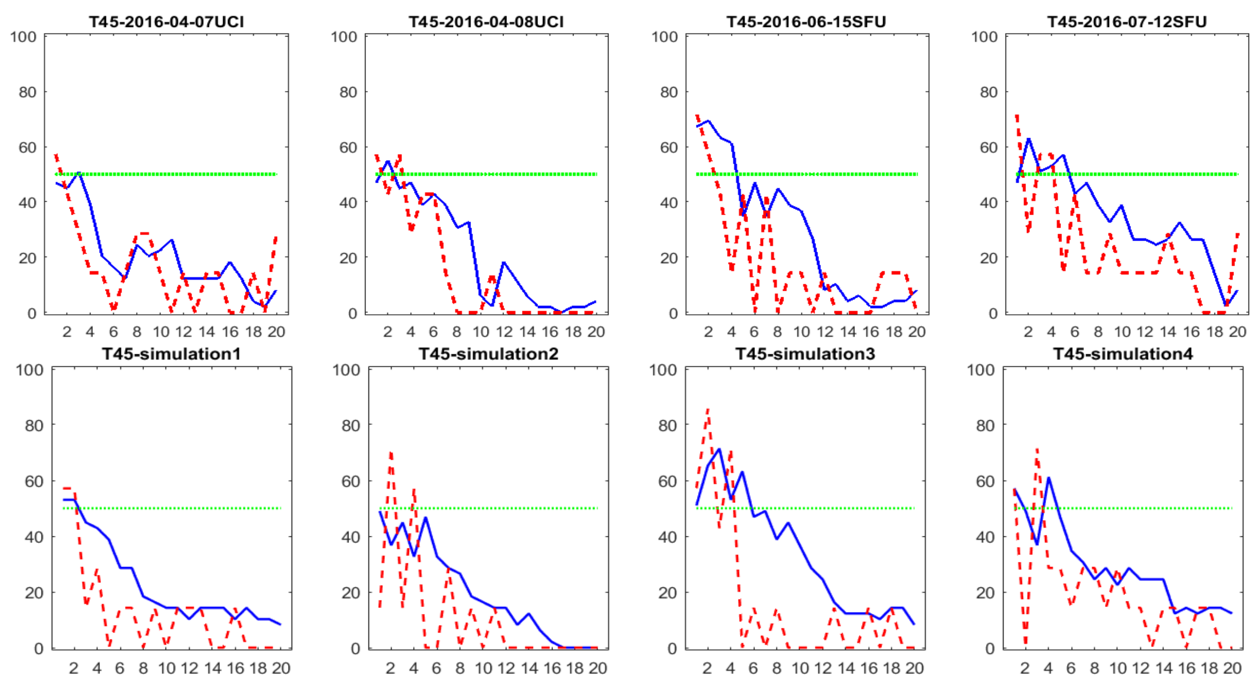
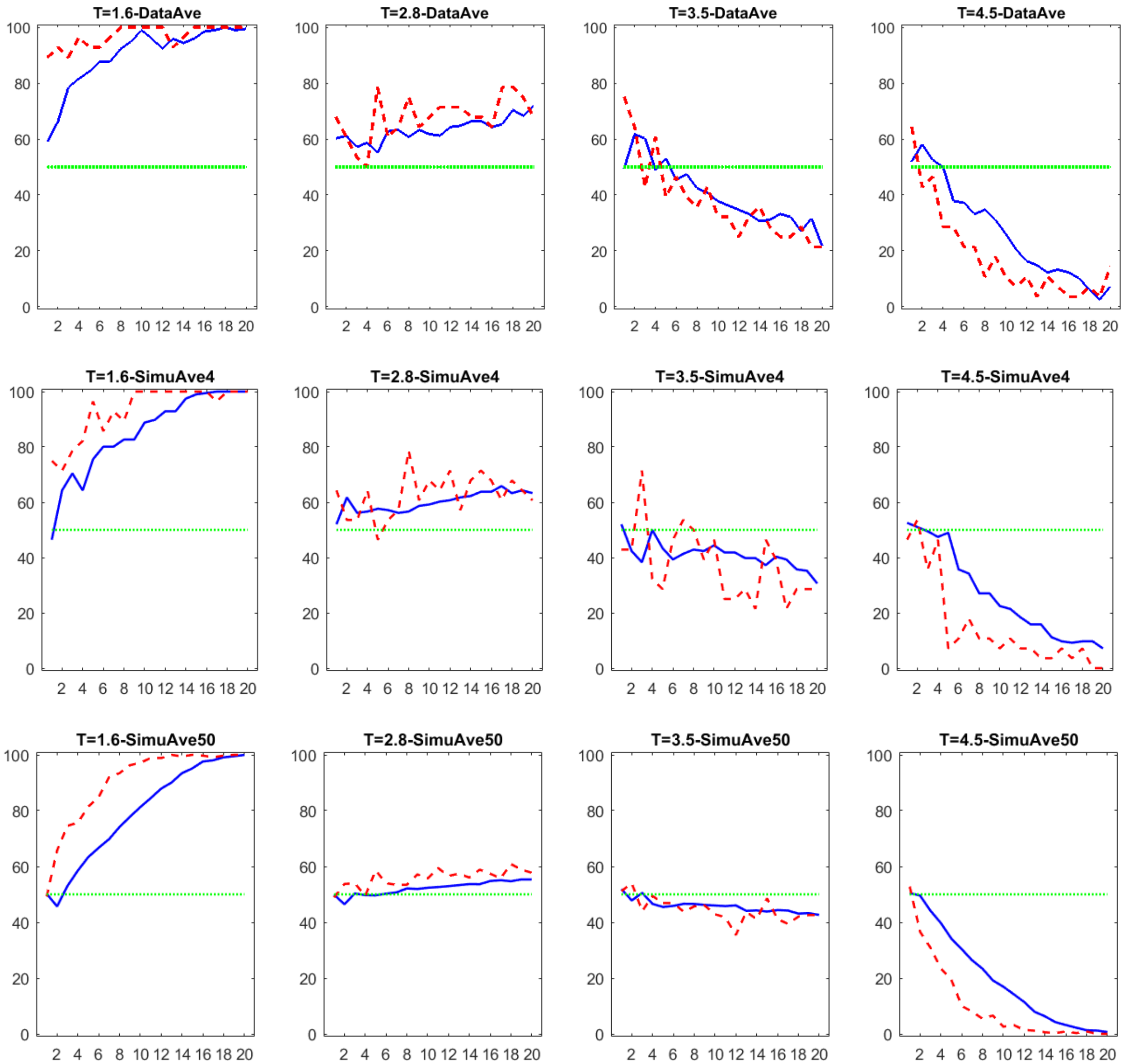


Figure 3d: Payment Choice in Sample Simulated Sessions T=4.5



Notes. (1) The 4 figures in the first row represent the 4 experimental sessions for reference, and the 4 figures in the second row represent sample simulated sessions under the IEL. (2) Horizontal axis: market. (3) The red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2.

Figure 4: Payment Choice Averaged across Simulated Sessions



Notes. (1) The 4 figures in the first row represent the average across the 4 experimental sessions for each of the 4 treatments; the 4 figures in the second row represent the average across the 4 sample simulated sessions shown in figure 3; and the 4 figures in the third row represent the average across 50 simulated sessions. (2) Horizontal axis: market. (3) The red dashed line represents the percentage of money allocated to payment 2, averaged across the seven buyers; the blue solid line represents the percentage of the seven sellers accepting payment 2.

Table 2: Payment Choice and Usage

		Treatment	T=1.6					T=2.8					T=3.5				
	Session		1	2	3	4	**all**	1	2	3	4	**all**	1	2	3	4	**all**
1		session mean	85	93	88	94	**90**	44	74	68	67	**63**	38	33	53	36	**40**
2	% of money	session min	53	53	65	63	**59**	37	55	61	49	**51**	6	14	39	22	**20**
3	allocated to	session max	100	100	100	100	**100**	57	96	80	76	**77**	71	65	71	57	**66**
4	payment 2	first market	53	53	67	63	**59**	57	73	61	49	**60**	65	49	39	45	**49**
5		last market	98	100	100	100	**99**	43	96	80	69	**72**	6	16	43	22	**22**
6		session mean	98	99	93	99	**97**	46	79	74	72	**68**	33	31	54	33	**38**
7	% of sellers	session min	86	86	71	86	**82**	29	29	57	43	**39**	0	0	29	14	**11**
8	accepting	session max	100	100	100	100	**100**	71	100	100	100	**93**	86	86	86	71	**82**
9	payment 2	first market	100	86	71	100	**89**	29	57	86	100	**68**	86	86	71	57	**75**
10		last market	100	100	100	100	**100**	29	86	86	71	**68**	0	14	43	29	**21**
11		session mean	84	92	86	93	**89**	38	67	62	64	**58**	29	23	45	28	**31**
12	% of meetings	session min	53	53	61	63	**58**	27	27	55	43	**38**	0	0	27	14	**10**
13	using	session max	100	100	100	100	**100**	49	92	76	71	**72**	63	53	59	49	**56**
14	payment 2	first market	53	53	63	63	**58**	27	55	61	49	**48**	63	49	39	41	**48**
15		last market	98	100	100	100	**99**	29	84	76	69	**64**	0	12	39	22	**18**
16		session mean	15	7	12	6	**10**	56	26	32	33	**37**	62	67	47	64	**60**
17	% of meetings	session min	0	0	0	0	**0**	43	4	20	24	**23**	29	35	29	43	**34**
18	using	session max	47	47	35	37	**41**	63	45	39	51	**49**	94	86	61	78	**80**
19	payment 1	first market	47	47	33	37	**41**	43	27	39	51	**40**	35	51	61	55	**51**
20		last market	2	0	0	0	**1**	57	4	20	31	**28**	94	84	57	78	**78**
21		session mean	1	1	2	1	**1**	6	7	6	3	**6**	9	9	8	8	**9**
22	% of meetings	session min	0	0	0	0	**0**	0	0	0	0	**0**	0	0	0	0	**0**
23	with no-trade	session max	12	14	14	12	**13**	31	43	22	22	**30**	22	51	31	43	**37**
24		first market	0	0	4	0	**1**	31	18	0	0	**12**	2	0	0	4	**2**
25		last market	0	0	0	0	**0**	14	12	4	0	**8**	6	4	4	0	**4**

Table 3: Efficiency

Part 1: payment-2 equilibrium as benchmark

	Treatment		T=1.6					T=2.8					T=3.5				
	Session		1	2	3	4	**all**	1	2	3	4	**all**	1	2	3	4	**all**
1		session mean	93	96	93	96	**94**	69	82	80	82	**78**	64	61	71	64	**65**
2		session min	79	79	75	84	**79**	50	44	68	62	**56**	43	27	51	38	**40**
3	buyer	session max	100	100	100	100	**100**	77	96	89	87	**88**	83	77	82	76	**80**
4		first market	79	79	81	84	**81**	50	70	83	77	**70**	83	77	73	71	**76**
5		last market	99	100	100	100	**100**	60	86	87	86	**80**	52	59	71	66	**62**
6		session mean	91	95	92	95	**93**	87	84	84	91	**86**	102	99	91	102	**98**
7		session min	72	73	76	78	**75**	68	56	69	59	**63**	79	61	63	68	**68**
8	seller	session max	100	100	100	100	**100**	95	93	94	100	**96**	121	114	105	118	**115**
9		first market	72	77	85	78	**78**	68	80	80	59	**72**	79	67	74	89	**77**
10		last market	99	100	100	100	**100**	86	86	88	98	**89**	117	114	105	112	**112**
11		session mean	92	96	92	96	**94**	75	82	81	85	**81**	75	72	77	75	**75**
12		session min	76	77	75	81	**77**	57	48	72	68	**61**	60	38	60	47	**51**
13	all	session max	100	100	100	100	**100**	82	95	87	92	**89**	87	81	86	84	**84**
14		first market	76	78	83	81	**80**	57	73	82	71	**71**	81	74	73	77	**76**
15		last market	99	100	100	100	**100**	69	86	87	91	**83**	72	76	81	80	**77**
	Part 2: payment-1 equilibrium as benchmark																
1		session mean	167	173	167	173	**170**	124	147	144	148	**141**	114	110	127	115	**116**
2		session min	142	142	135	151	**143**	91	78	123	112	**101**	78	49	92	69	**72**
3	buyer	session max	180	180	180	180	**180**	139	173	160	157	**158**	149	139	147	137	**143**
4		first market	142	142	147	151	**146**	91	126	149	139	**126**	149	139	131	129	**137**
5		last market	178	180	180	180	**180**	109	155	156	156	**144**	94	106	127	118	**111**
6		session mean	122	128	124	128	**126**	87	84	84	91	**86**	82	79	73	82	**79**
7		session min	97	98	102	105	**101**	68	56	69	59	**63**	63	49	50	54	**54**
8	seller	session max	134	134	134	134	**134**	95	93	94	100	**96**	97	91	84	94	**92**
9		first market	97	103	114	105	**105**	68	80	80	59	**72**	63	53	60	71	**62**
10		last market	133	134	134	134	**134**	86	86	88	98	**89**	94	91	84	89	**90**
11		session mean	144	151	145	151	**148**	105	115	114	120	**114**	98	94	100	98	**98**
12	all	session min	120	121	118	128	**122**	79	67	100	95	**85**	78	49	78	61	**66**
13		session max	157	157	157	157	**157**	114	133	122	129	**125**	113	105	112	109	**110**
14		first market	120	123	130	128	**125**	79	103	115	99	**99**	106	96	95	100	**99**
15		last market	156	157	157	157	**157**	97	120	122	127	**117**	94	99	106	104	**100**

Table 4: Rank-sum Test – Treatment Effect

		group 1	group 2	z-value	p-value
T=1.6 versus T=2.8					
	BuyerChoice	26	10	2.309	0.021
Session average	SellerAccept	26	10	2.323	0.020
	Pay2Meetings	26	10	2.309	0.021
	BuyerChoice	18	18	0	1
First market	SellerAccept	21.5	14.5	1.042	0.298
	Pay2Meetings	22	14	1.169	0.243
T=2.8 versus T=3.5					
	BuyerChoice	25	11	2.021	0.043
Session average	SellerAccept	25	11	2.033	0.042
	Pay2Meetings	25	11	2.021	0.043
	BuyerChoice	22.5	13.5	1.307	0.191
First market	SellerAccept	18.5	17.5	0.149	0.882
	Pay2Meetings	18.5	17.5	0.145	0.885
T=1.6 versus T=3.5					
	BuyerChoice	26	10	2.309	0.021
Session average	SellerAccept	26	10	2.337	0.019
	Pay2Meetings	26	10	2.309	0.021
	BuyerChoice	23	13	1.452	0.147
First market	SellerAccept	22.5	13.5	1.348	0.178
	Pay2Meetings	23	13	1.488	0.137

Notes. (1) Combined sample size for each test is 8.

Table 5: Buyer Payment 2 Choice (%) with Random Effects

Independent variables	statistics	(1) pooled	(2) T=1.6	(3) T=2.8	(4) T=3.5
	Coef.	**0.218** ***	**0.328** ***	**0.100** ***	**0.174** ***
MktAcceptL(%)	Std.Err.	0.021	0.108	0.027	0.025
	t	10.33	3.02	3.64	6.82
	p	0.000	0.002	0.000	0.000
	Coef.	**0.593** ***	**0.400** ***	**0.624** ***	**0.567** ***
bBelief(%)	Std.Err.	0.021	0.048	0.034	0.029
	t	27.90	8.29	18.34	19.68
	p	0.000	0.000	0.000	0.000
	Coef.	**0.129** ***	**0.699** ***	**0.197** ***	**-0.404** ***
market	Std.Err.	0.049	0.124	0.072	0.086
	t	2.64	5.64	2.75	-4.71
	p	0.008	0.000	0.006	0.000
	Coef.	**1.787**	**4.624** **	**5.575** ***	**-3.731** **
location	Std.Err.	1.212	2.140	2.151	1.823
(SFU=1;UCI=0)	t	1.47	2.16	2.59	-2.05
	p	0.140	0.031	0.01	0.041
	Coef.	**5.174** ***			
T16	Std.Err.	1.591			
	t	3.25			
	p	0.001			
	Coef.	**-4.042** ***			
T35	Std.Err.	1.578			
	t	-2.56			
	p	0.010			
No. of obs.		1596	532	532	532
Overall R^2		0.825	0.355	0.687	0.764

Notes. (1) *p-value<=0.1; **p-value<=0.05; *** p-value<=0.01.

Table 6: Seller Acceptance (1=Accept, 0=Reject), Probit with Random Effects

Independent variables	statistics	(1) pooled	(2) T=1.6	(3) T=2.8	(4) T=3.5
sOtherAcceptL(%)	**dy/dx**	**0.032**	**0.043**	**-0.168**	**-0.046**
	Std.Err.	0.054	0.078	0.116	0.123
	t	0.60	0.55	-1.45	-0.38
	p	0.551	0.582	0.146	0.706
sAcceptL*sCardDealL(%)	**dy/dx**	**0.151** ***	**0.033**	**-0.025**	**0.276** ***
	Std.Err.	0.033	0.037	0.071	0.065
	t	4.56	0.91	-0.35	4.22
	p	0.000	0.363	0.723	0.000
(1-sAcceptL)*sNoDealL(%)	**dy/dx**	**0.446** ***	**0.369**	**0.065**	**0.764** ***
	Std.Err.	0.088	0.282	0.184	0.172
	t	5.09	1.31	0.35	4.44
	p	0.000	0.190	0.724	0.000
sBeliefB(%)	**dy/dx**	**0.366** ***	**0.062**	**0.535** ***	**0.470** ***
	Std.Err.	0.0465	0.040	0.097	0.088
	t	7.87	1.57	5.52	5.32
	p	0.000	0.117	0.000	0.000
sBeliefS(%)	**dy/dx**	**0.219** ***	**0.115** **	**0.283** **	**0.208** **
	Std.Err.	0.049	0.052	0.111	0.087
	t	4.47	2.23	2.54	2.39
	p	0.000	0.026	0.011	0.017
market	dy/dx	**0.246**	**0.059**	**0.981** ***	**-0.621**
	Std.Err.	0.159	0.179	0.310	0.448
	t	1.55	0.33	3.17	-1.39
	p	0.121	0.742	0.002	0.165
location (SFU=1;UCI=0)	**dy/dx**	**0.446**	**-0.123**	**3.471**	**0.524**
	Std.Err.	3.582	1.707	10.006	7.373
	t	0.12	-0.07	0.35	0.07
	p	0.901	0.943	0.729	0.943
T16	**dy/dx**	**19.261** ***			
	Std.Err.	5.210			
	t	3.70			
	p	0.000			
T35	**dy/dx**	**-9.874** **			
	Std.Err.	3.944			
	t	-2.50			
	p	0.012			
No. of obs.		1596	532	532	532

Notes. (1) dy/dx represents the marginal effect of the independent variable on the probability (in %) of a seller accepting payment 2; (2) *p-value<=0.1, **p-value<=0.05, *** p-value<=0.01.

Table 7 : Payment Choice and Usage T=4.5

		Session	1	2	3	4	**all**
1		Session mean	21	22	29	34	**26**
2	% of money	Session min	2	0	2	2	**2**
3	allocated to	Session max	51	55	69	63	**60**
4	payment 2	first market	47	47	67	47	**52**
5		last market	8	4	8	8	**7**
6		Session mean	16	15	18	24	**18**
7	% of sellers	Session min	0	0	0	0	**0**
8	accepting	Session max	57	57	71	71	**64**
9	payment 2	first market	57	57	71	71	**64**
10		last market	29	0	0	29	**14**
11		Session mean	12	12	14	20	**14**
12	% of meetings	Session min	0	0	0	0	**0**
13	using	Session max	41	41	61	51	**48**
14	Payment 2	first market	41	41	61	45	**47**
15		last market	8	0	0	8	**4**
16		Session mean	79	78	71	66	**74**
17	% of meetings	Session min	49	45	31	37	**40**
18	using	Session max	98	100	98	98	**98**
19	payment 1	first market	53	53	33	53	**48**
20		last market	92	96	92	92	**93**
21		Session mean	9	10	15	15	**12**
22	% of meetings	Session min	0	0	0	0	**0**
23	with no-trade	Session max	27	33	47	43	**37**
24		first market	6	6	6	2	**5**
25		last market	0	4	8	0	**3**

Table 8: Efficiency T=4.5

		Session	1	2	3	4	**all**
Part 1: payment-2 equilibrium as benchmark							
1		session mean	55	55	53	56	**55**
2		session min	41	37	29	38	**36**
3	buyer	session max	70	71	79	77	**75**
4		first market	70	70	79	74	**74**
5		last market	59	53	51	59	**56**
6		session mean	153	155	142	137	**147**
7		session min	103	103	90	82	**94**
8	seller	session max	190	194	190	190	**191**
9		first market	103	103	99	82	**97**
10		last market	136	187	179	136	**159**
11		session mean	77	77	73	74	**75**
12		session min	63	58	46	51	**55**
13	all	session max	85	86	85	88	**86**
14		first market	78	78	84	76	**79**
15		last market	76	83	79	76	**79**
Part 2: payment-1 equilibrium as benchmark							
1		session mean	100	99	96	101	**99**
2		session min	73	67	53	69	**66**
3	buyer	session max	127	129	143	139	**134**
4		first market	127	127	143	134	**132**
5		last market	107	96	92	107	**100**
6		session mean	79	80	73	71	**76**
7		session min	53	53	46	42	**49**
8	seller	session max	98	100	98	98	**98**
9		first market	53	53	51	42	**50**
10		last market	70	96	92	70	**82**
11		session mean	89	90	84	86	**87**
12	all	session min	73	67	53	59	**63**
13		session max	98	100	98	102	**99**
14		first market	90	90	97	88	**91**
15		last market	88	96	92	88	**91**

Table 9: Buyer Payment 2 Choice (%) with Random Effects T=4.5

Independent variables	statistics		
	Coef.	**-0.002**	
MktAcceptL(%)	Std.Err.	0.046	
	t	-0.03	
	p	0.973	
	Coef.	**0.766**	***
bBelief(%)	Std.Err.	0.043	
	t	17.67	
	p	0.000	
	Coef.	**-0.619**	***
market	Std.Err.	0.156	
	t	-3.97	
	p	0.000	
	Coef.	**3.905**	*
location (SFU=1;UCI=0)	Std.Err.	2.222	
	t	1.76	
	p	0.079	
No. of obs.		532	
Overall R^2		0.714	

Notes. (1) *p-value<=0.1, **p-value<=0.05, *** p-value<=0.01.

Table 10: Seller Acceptance (1=Accept, 0=Reject), Probit with Random Effects T=4.5

Independent variables	statistics		
sOtherAcceptL(%)	**dy/dx**	**0.047**	
	Std.Err.	0.108	
	t	0.43	
	p	0.665	
sAcceptL*sCardDealL(%)	**dy/dx**	**0.110**	*
	Std.Err.	0.062	
	t	1.79	
	p	0.073	
(1-sAcceptL)*sNoDealL(%)	**dy/dx**	**0.254**	**
	Std.Err.	0.125	
	t	2.03	
	p	0.043	
sBeliefB(%)	**dy/dx**	**0.194**	***
	Std.Err.	0.065	
	t	2.99	
	p	0.003	
sBeliefS(%)	**dy/dx**	**0.269**	***
	Std.Err.	0.067	
	t	3.99	
	p	0.000	
market	dy/dx	**0.257**	
	Std.Err.	0.522	
	t	0.49	
	p	0.623	
location (SFU=1;UCI=0)	**dy/dx**	**1.742**	
	Std.Err.	4.400	
	t	0.40	
	p	0.692	
No. of obs.		532	

Notes. (1) dy/dx represents the marginal effect of the independent variable on the probability (in %) of a seller accepting payment 2; (2) *p-value<=0.1, **p-value<=0.05, *** p-value<=0.01.

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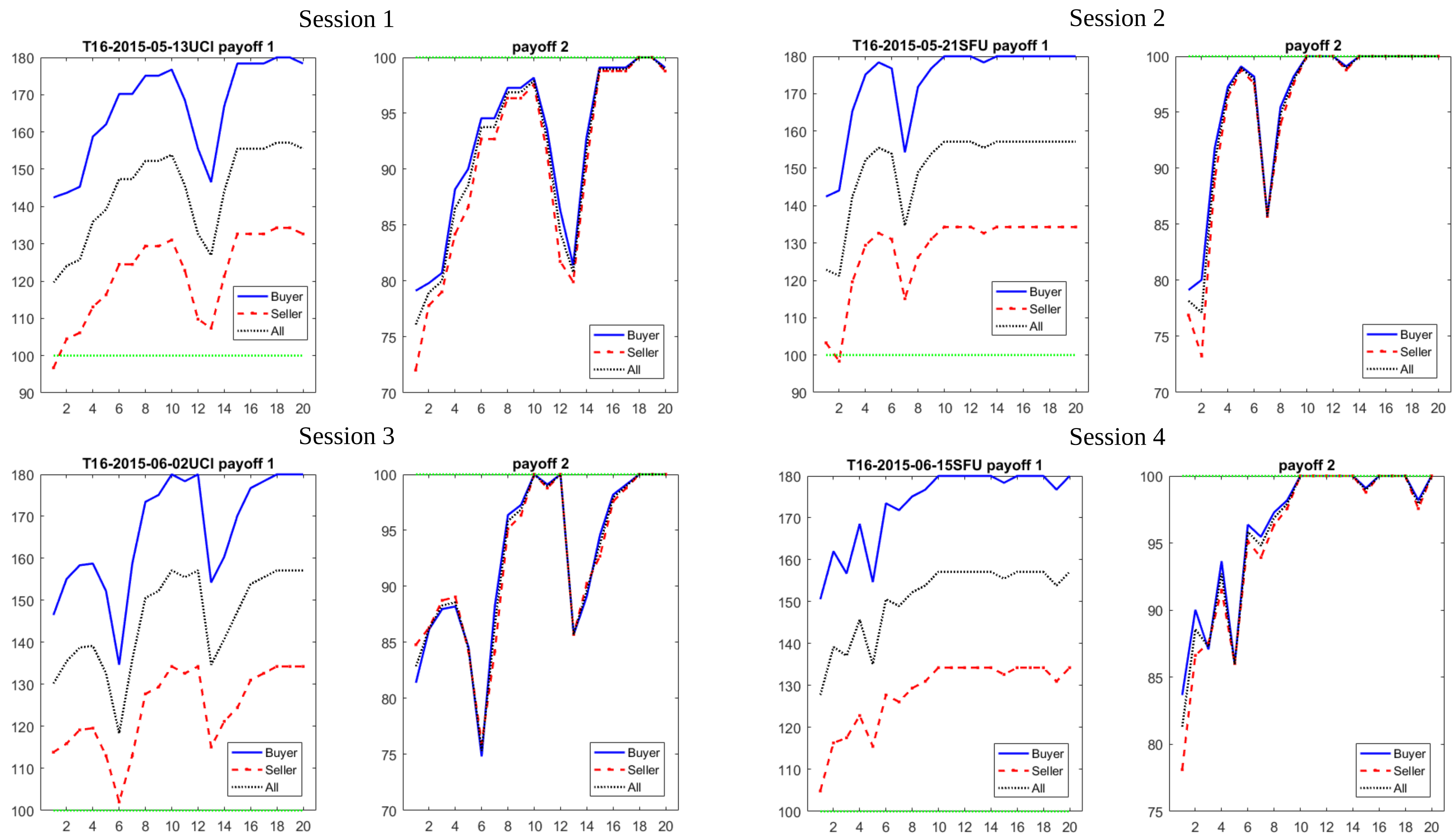
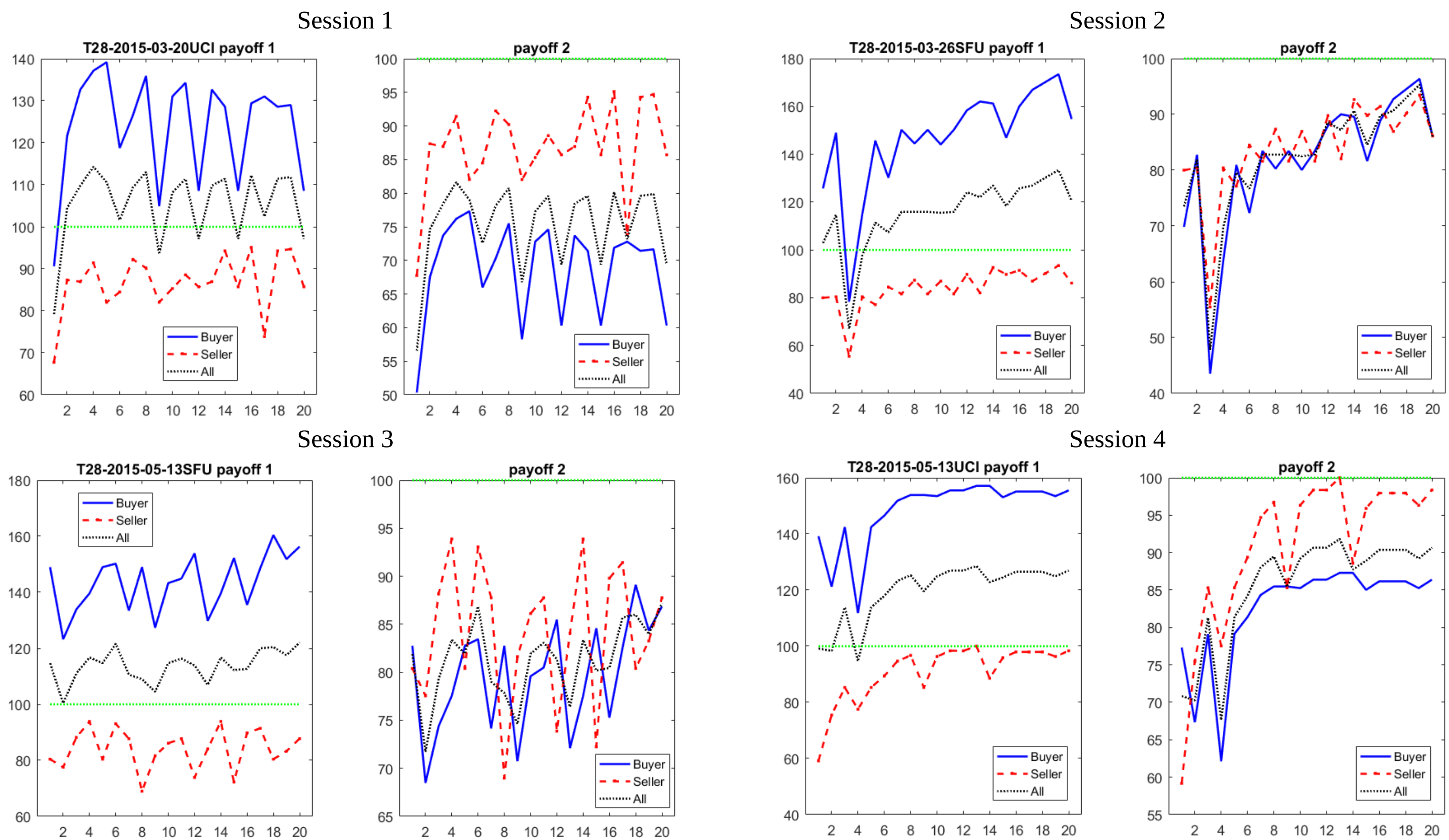
Appendix A: Additional Figures and Tables

Figure Aa: Efficiency T=1.6



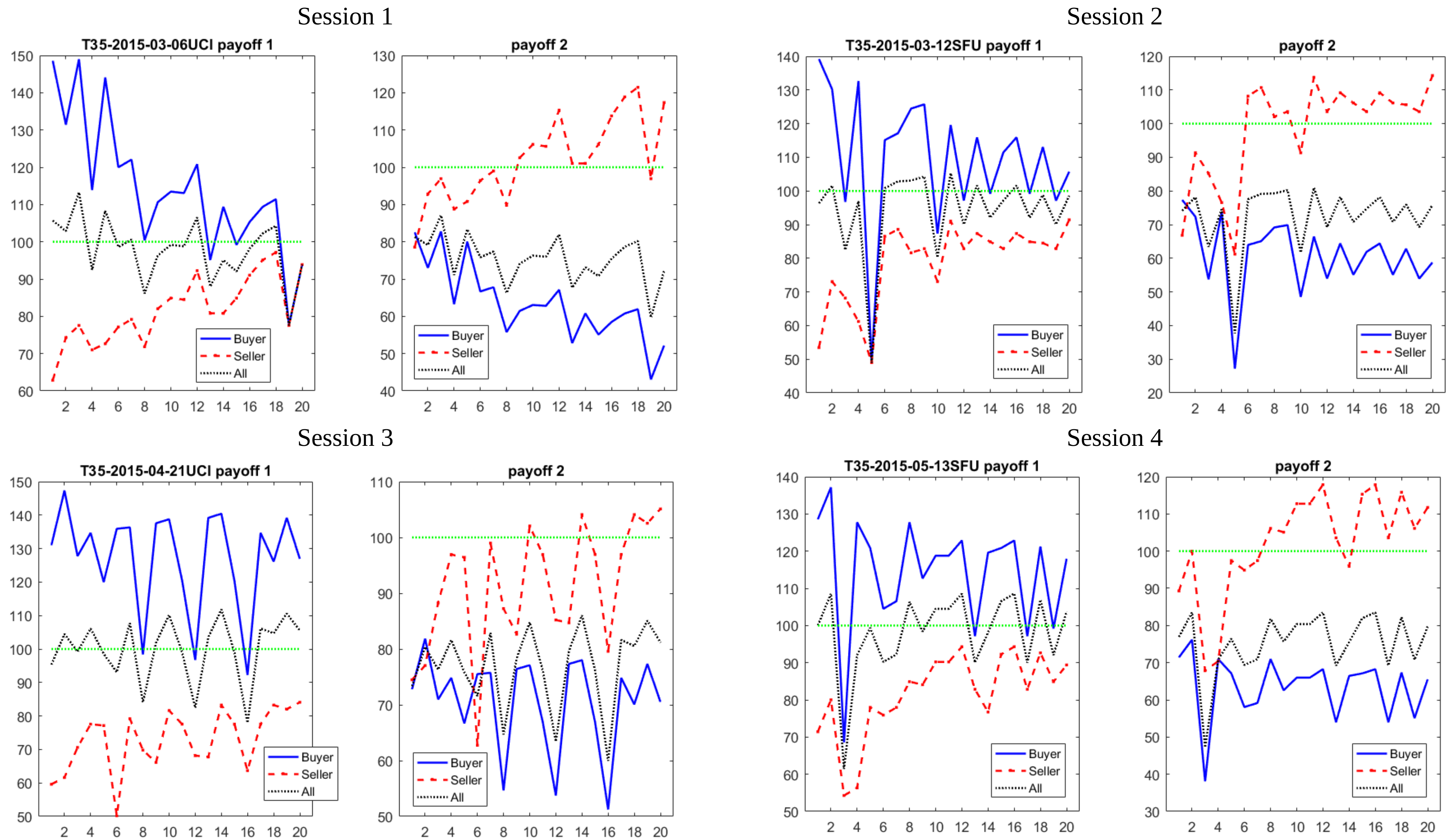
Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first figure measures efficiency using payoffs in the payment-1 equilibrium as the benchmark (100%). The blue solid line represents sellers, the red dashed line represents buyers and the black line marked with circles represents buyers and sellers together. The second figure measures efficiency using payoffs in the payment-2 equilibrium as the benchmark.

Figure Ab: Efficiency T=2.8



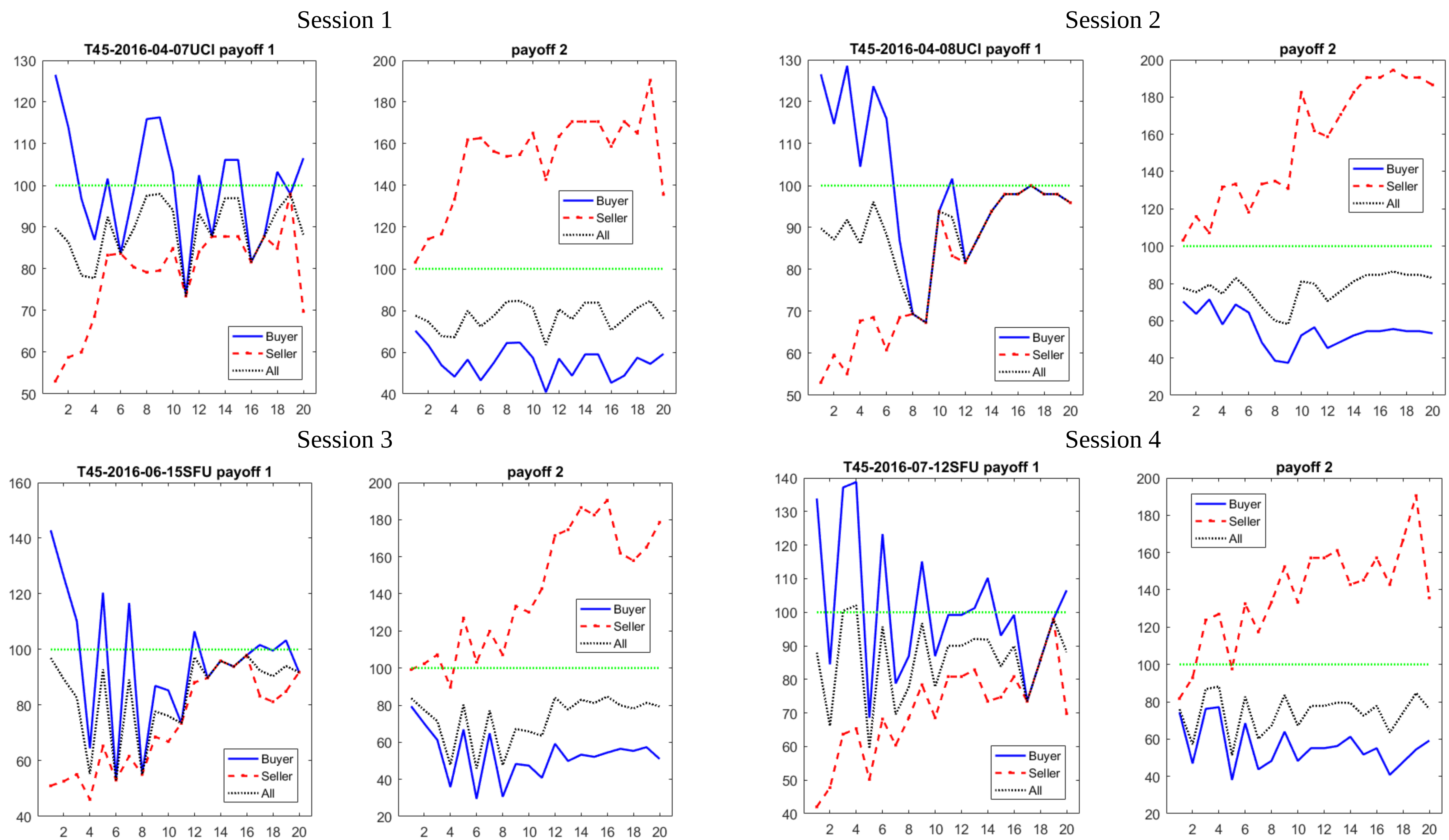
Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first figure measures efficiency using payoffs in the payment-1 equilibrium as the benchmark (100%). The blue solid line represents sellers, the red dashed line represents buyers and the black line marked with circles represents buyers and sellers together. The second figure measures efficiency using payoffs in the payment-2 equilibrium as the benchmark.

Figure Ac: Efficiency T=3.5



Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first figure measures efficiency using payoffs in the payment-1 equilibrium as the benchmark (100%). The blue solid line represents sellers, the red dashed line represents buyers and the black line marked with circles represents buyers and sellers together. The second figure measures efficiency using payoffs in the payment-2 equilibrium as the benchmark.

Figure Ad: Efficiency T=4.5



Notes. (1) Horizontal axis: market. (2) There are two figures for each session. The first figure measures efficiency using payoffs in the payment-1 equilibrium as the benchmark (100%). The blue solid line represents sellers, the red dashed line represents buyers and the black line marked with circles represents buyers and sellers together. The second figure measures efficiency using payoffs in the payment-2 equilibrium as the benchmark.

Table A1: Interaction Between Buyers and Sellers, Conditional Mixed Process Estimator

Independent variables	statistics	(1)		(2)		(3)		(4)	
Buyer payment 2 choice (%) with random effects									
MktAcceptL(%)	**Coef.**	**0.218**	***			**0.534**	***		
	Std.Err.	0.047				0.051			
bBelief(%)	**Coef.**	**0.592**	***	**0.712**	***				
	Std.Err.	0.046		0.038					
market	**Coef.**	**0.129**		**0.066**		**0.212**		**0.054**	
	Std.Err.	0.115		0.119		0.157		0.216	
location (SFU=1;UCI=0)	**Coef.**	**1.794**		**2.045**		**2.368**		**3.645**	
	Std.Err.	1.253		1.306		1.713		2.366	
T16	**Coef.**	**5.197**	***	**8.137**	***	**12.720**	***	**28.181**	***
	Std.Err.	1.927		1.927		2.560		2.898	
T35	**Coef.**	**-4.066**	**	**-7.704**	***	**-8.420**	***	**-24.089**	***
	Std.Err.	1.890		1.824		2.572		2.898	
Seller acceptance (1=accept, 0=reject), probit with random effects									
sOtherAcceptL(%)	**dy/dx**	**0.038**				**0.247**	**		
	Std.Err.	0.116				0.104			
sAcceptL*sCardDealL(%)	**dy/dx**	**0.162**	**			**0.302**	***		
	Std.Err.	0.065				0.055			
(1-sAcceptL)*sNoDealL(%)	**dy/dx**	**0.478**	**			**0.723**	***		
	Std.Err.	0.192				0.186			
sBeliefB(%)	**dy/dx**	**0.396**	***	**0.444**	***				
	Std.Err.	0.093		0.100					
sBeliefS(%)	**dy/dx**	**0.235**	**	**0.300**	***				
	Std.Err.	0.104		0.104					
market	dy/dx	**0.272**		**0.163**		**0.263**		**-0.029**	
	Std.Err.	0.004		0.408		0.372		0.486	
location (SFU=1;UCI=0)	**dy/dx**	**0.355**		**0.880**		**1.464**		**3.469**	
	Std.Err.	3.888		4.495		3.990		5.363	
T16	**dy/dx**	**20.860**	***	**23.885**	***	**25.076**	***	**43.428**	***
	Std.Err.	6.704		7.334		7.048		8.643	
T35	**dy/dx**	**-10.556**	**	**-12.245**	**	**-12.495**	**	**-25.692**	***
	Std.Err.	4.880		4.843		5.111		4.345	
No. of obs.		1596		1596		1596		1596	
Residuals cross-eqn correlation		**0.034**		**0.028**		**0.055**		**0.170**	***
Std.Err.		0.052		0.053		0.045		0.041	

Notes. (1) dy/dx represents the marginal effect of the independent variable on the probability (in %) of a seller accepting payment 2; (2) *p-value<=0.1, **p-value<=0.05, *** p-value<=0.01.

Table A2: State Dependence – Buyers

Independent variables	statistics	(1)	(2)	(3)	(4)
Buyer payment 2 choice (%)					
bcardL(%)	**Coef.**	**0.672** ***	**0.383** ***	**0.527** ***	**0.372** ***
	Std.Err.	0.018	0.017	0.017	0.017
MktAcceptL(%)	**Coef.**			**0.404** ***	**0.203** ***
	Std.Err.			0.018	0.019
bBelief(%)	**Coef.**		**0.546** ***		**0.429** ***
	Std.Err.		0.019		0.021
market	**Coef.**	**-0.079**	**-0.012**	**0.069**	**0.048**
	Std.Err.	0.060	0.049	0.053	0.047
location (SFU=1;UCI=0)	**Coef.**	**1.432** **	**1.160** **	**0.943**	**0.973** *
	Std.Err.	0.661	0.534	0.579	0.517
T16	**Coef.**	**10.255** ***	**2.615** ***	**2.409** ***	**0.309**
	Std.Err.	0.935	0.800	0.894	0.804
T35	**Coef.**	**-9.287** ***	**-3.107** ***	**-0.613**	**-0.075**
	Std.Err.	0.896	0.755	0.879	0.784

Table A3: State Dependence – Sellers

Independent variables	statistics	(1)	(2)	(3)	(4)
Seller acceptance (1=accept, 0=reject), probit					
sAcceptL	**dy/dx**	**25.587** ***	**18.219** ***	**18.471** ***	**5.262**
	Std.Err.	1.512	1.624	6.215	5.965
sOtherAcceptL(%)	**dy/dx**			**0.181** ***	**0.001**
	Std.Err.			0.044	0.050
sAcceptL*sCardDealL(%)	**dy/dx**			**0.415** ***	**0.275** ***
	Std.Err.			0.068	0.067
(1-sAcceptL)*sNoDealL(%	**dy/dx**			**0.775** ***	**0.593** ***
	Std.Err.			0.079	0.082
sBeliefB(%)	**dy/dx**		**0.331** ***		**0.291** ***
	Std.Err.		0.040		0.040
sBeliefS(%)	**dy/dx**		**0.185** ***		**0.150** ***
	Std.Err.		0.041		0.045
market	dy/dx	**0.022**	**0.140**	**0.219**	**0.204**
	Std.Err.	0.165	0.158	0.165	0.160
location (SFU=1;UCI=0)	**dy/dx**	**2.207**	**1.589**	**0.879**	**0.786**
	Std.Err.	1.815	1.736	1.716	1.677
T16	**dy/dx**	**26.478** ***	**17.199** ***	**17.527** ***	**15.923** ***
	Std.Err.	2.969	3.057	3.127	3.969
T35	**dy/dx**	**-13.699** ***	**-7.700** ***	**-7.394** ***	**-7.780** ***
	Std.Err.	1.857	1.876	2.158	2.049
No. of obs.		1596	1596	1596	1596

Notes. (1) dy/dx represents the marginal effect of the independent variable on the probability (in %) of a seller accepting payment 2; (2) *p-value<=0.1, **p-value<=0.05, *** p-value<=0.01.

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Appendix B: Seller Belief Formation in IEL

In this Appendix, we describe the process by which sellers update their expectations of the average amount that buyers allocated to payment 2, $s^f\bar{m}_b^i(t)$. This is carried out in four steps.

Step 1. Infer the boundaries on the initial payment 2 allocation of each trading partner (one for each of the seven rounds of transaction) in the past market.

Note that in the experiment, a seller does not know a buyer's initial payment allocation and must infer it with a limited information set, which includes (i) whether the seller herself accepted payment 2 or not, (ii) how many of the other six sellers chose to accept payment 2, (iii) in which round (out of seven) she meets the buyer, and (iv) whether the transaction uses payment 1, payment 2 or fails to take place. In many situations, the seller will not be able to pinpoint the buyer's initial choice exactly, but she can always infer either the lower bound (call it a *Min inference*) or the upper bound (call it a *Max inference*) of the buyer's payment 2 allocation.

Let r refer to the current round, M to the number of sellers ($M = 7$), and $s_a^{-i}(t)$ the number of other sellers who accepted payment 2 in the past market. Table B summarizes what the seller can infer about her round r trading partner's initial payment 2 allocation (assuming that the buyer behaves optimally). There are four cases to consider, with the first two applying to a seller who did not accept payment 2, and the other two cases applying to a seller who accepted payment 2.

Table B: Seller's guess about buyer's initial payment 2 allocation

Case	Transaction	P2 Accepted?	Buyer initial P2 allocation
A	None	No	Min: $m_b \geq 8 - r + (r-1) * s_a^{-i}(t)/(M-1)$
B	Use P1	No	Max: $m_b \leq 7 - r + (r-1) * s_a^{-i}(t)/(M-1)$
C	Use P1	Yes	Max: $m_b \leq (r-1) * s_a^{-i}(t)/(M-1)$
D	Use P2	Yes	Min: $m_b \geq 1 + (r-1) * s_a^{-i}(t)/(M-1)$

Notes: P1 (P2) is short for payment 1 (payment 2).

In case A, the seller chose not to accept payment 2 and no transaction occurred for the round in question. The seller knows that the buyer in that round had no payment 1 available – this implies a maximum that the buyer allocated to payment 1 at the beginning of the market, or a minimum allocated to payment 2. The value of this minimum is given by $8 - r + (r-1) * s_a^{-i}(t)/(M-1)$. We illustrate this case with two examples, one assuming that all other sellers accepted payment 2, or $s_a^{-i}(t) = 6$, and the other assuming that none of the other sellers accepted payment 2, or $s_a^{-i}(t) = 0$ (and we do the same with the other three cases).

Example A1. Suppose $s_a^{-i}(t) = 6$. The seller knows that no matter which round it is, the buyer had not needed to spend payment 1 until the buyer met the seller herself. If the buyer did not have payment 1, it is because he chose to allocate all his 7 units to payment 2. In this example, the seller can infer exactly that the buyer chose $m_b = 7$.

Example A2. Suppose $s_a^{-i}(t) = 0$. The seller's guess depends on the round of the transaction. If $r = 1$, then the seller knows exactly that the buyer's payment 2 allocation was $8 - 1 = 7$ (and the initial balance of payment 1 is 0). If $r = 2$, then the buyer's initial payment 1 balance could be either 0 (in which case he did not trade in the first round), or 1 (in which case he paid with payment 1 in the first round); equivalently, his initial payment 2 allocation was either 6 or 7 (so the minimum is $8 - 2 = 6$). For each round, going further in time, the seller has less and less precise information about the buyer's initial choice because she does not know how *many times the buyer has used payment 1 in the previous rounds*.

In case B, the seller did not accept P2 and a transaction took place with P1. Since the buyer had P1 to use, there was a minimum that this buyer allocated to P1, or a maximum allocated to P2. The value of this maximum is given by $7 - r + (r-1) * s_a^{-i}(t)/(M-1)$.

Example B1. Suppose $s_a^{-i}(t) = 6$. The seller knows that the buyer initially allocated at least 1 unit of payment 1, but this is all she can infer: the buyer could have more payment 1 in hand to spend in later rounds and/or might have have spent some payment 1 in previous rounds. Equivalently, the seller can only infer that the buyer had initially at most 6 units in payment 2.

Example B2. Suppose $s_a^{-i}(t) = 0$. The seller can infer that the buyer initially allocated at least r units of payment 1 if he still has payment 1 to spend in round r. Equivalently, the buyer allocated at most $7 - r$ units in payment 2 initially. As the round number increases, the seller acquires more precise information about the buyer's initial choice. If the buyer still had payment 1 in round 7, then the seller knows exactly that the buyer chose to allocate all his money to payment 1 and nothing to payment 2.

In case C, the seller accepted payment 2 but the buyer used payment 1. This implies that the buyer had no payment 2 left. This sets a maximum on how much the buyer allocated to payment 2. The value of the maximum is given by: $(r-1) * s_a^{-i}(t)/(M-1)$.

Example C1. Suppose $s_a^{-i}(t) = 6$. The seller knows that the buyer ran out of payment 2 in previous rounds, but she is not sure how many times the buyer had used payment 2 in the previous rounds: the number can vary from 0 to $r - 1$. As the round goes on, the seller's inference becomes less accurate.

Example C1. Suppose $s_a^{-i}(t) = 0$. The seller can infer exactly that the buyer allocated nothing to payment 2 irrespective of which round it is because the buyer could not spend payment 2 in previous rounds.

In case D, the seller accepted payment 2, and the buyer paid using payment 2. This implies that there is a minimum amount that the buyer allocated to payment 2. The value of the limit is given by $1 + (r-1) * s_a^{-i}(t)/(M-1)$.

Example D1. Suppose $s_a^{-i}(t) = 6$. Since the buyer still had payment 2 in round r, the seller can infer that the buyer had at least r units of payment 2 initially. As the round number increases, the seller has more accurate information about the buyer's portfolio choice. In round 7, the seller knows that the buyer chose to allocate all his money to payment 2.

Example D2. Suppose $s_a^{-i}(t) = 0$. The seller's inference about the buyer's initial portfolio choice is very imprecise: she only knows the buyer has at least 1 unit of payment 2 to spend in this round, but has no idea whether the buyer had used payment 2 in previous rounds and still had more payment 2 to spend in later rounds.

Step 2. Evaluate the accurateness of the seven inferences in step 1. A Min (Max) inference with a larger (smaller) bound implies a smaller set of possible values for the buyer's P2 (and P1) allocation and is more accurate. We use the *certainty value* (CE) to quantify the accurateness of these inferences. The CE is calculated as 8 minus the number of elements in the set of possible values of the buyer's payment 2 allocation; as a result, a smaller set is awarded a higher CE. For example, an inference with $m_b \geq 7$ implies a set with a single element {7}, so its CE is $8 - 1 = 7$. An inference with $m_b \leq 4$ implies the set $\{0, 1, 2, 3, 4\}$ with 5 elements, so its CE is $8 - 5 = 3$. Equivalently, the following formula can be used to calculate the CE:

$$CE = \begin{cases} x \text{ for inference } m_b \geq x, \\ 7 - x \text{ for inference } m_b \leq x. \end{cases}$$

Step 3. Use the lower and upper bounds for the seven inferences to estimate the lower and upper bounds for the "average" buyer. The "average" lower (upper) bound is calculated as the sum of the lower (upper) bounds of all Min (Max) inferences, weighted by their CEs calculated in step 2.

Step 4. The final step is to use the "average" lower and upper bounds to calculate the expectation about the average buyer's P2 allocation, $s^f \bar{m}_b^i(t)$, as the weighted sum of the two "average" bounds, with the weight of the lower (upper) average bound being given by the number of Min (Max) inferences.

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Appendix C: Experiment Instructions *(T=2.8 treatment only; other treatments are similar)*

Welcome to this experiment in economic decision-making. Please read these instructions carefully as they explain how you earn money from the decisions that you make. You are guaranteed $7 for showing up and completing the study. Additional earnings depend on your decisions and on the decisions of other participants as explained below. You will be earning experimental money (EM). At the end of the experiment, you will be paid in dollars at the exchange rate of 1 EM = $0.15.

There are 14 participants in today's experiment: 7 will be randomly assigned the role of buyers and 7 the role of sellers. You will learn your role at the start of the experiment, and remain in the *same* role for the duration of the experiment. Buyers and sellers will interact in 20 "markets" to trade goods for payment. There are two payment methods, payment 1 and payment 2.

Each market consists of two stages. The first is the payment choice stage. Each buyer is endowed with 7 EM and decides how to allocate it between the two payment methods. Each seller is endowed with 7 units of goods. Sellers have to accept payment 1, but can decide whether or not to accept payment 2. Sellers who decide to accept payment 2 have to pay a one-time fee of 2.8 EM. No participant observes any seller's choice at this stage.

The second stage is the trading stage, which consists of a sequence of 7 rounds. In these 7 rounds, you meet with each of the 7 participants who are in the opposite role to yourself sequentially and in a random order. In each meeting you try to trade one unit of good for one unit of payment. The buyer decides which payment to use and the trade is successful if and only if the seller accepts the payment offered by the buyer. For each successful sale or purchase, you earn 1 EM less some transaction costs. The transaction cost to both sides is 0.5 EM if payment 1 is used, and 0.1 EM if payment 2 is used. If the buyer offers payment 1 (which is always accepted by sellers), then trade is successful and both the buyer and the seller earn a *net* payoff of 1-0.5=0.5 EM. If the buyer offers payment 2 and the seller has decided to accept payment 2 in the first stage, then trade is again successful and both earn a *net* payoff of 1-0.1=0.9 EM. If the buyer has only payment 2 and the seller has decided not to accept it, then no trade can take place and both earn 0 EM. At the end of the market, unspent EMs or unsold goods have no redemption value and do not entitle you to extra earnings.

Task summary

<table>
<tr><td rowspan="2">Market 1</td><td>Stage 1: Payment choice
Buyers allocate 7 EM between the two payments
Sellers decide whether to accept payment 2 at a one-time fee of 2.8 EM</td></tr>
<tr><td>Stage 2: Trading (7 rounds)
Each buyer meets each of the 7 sellers in a random order
Trade with payment 1 → net payoff of 0.5 EM
Trade with payment 2 → net payoff of 0.9 EM
No trade → net payoff of 0 EM</td></tr>
<tr><td rowspan="2">Market 2</td><td>Stage 1: Payment choice</td></tr>
<tr><td>Stage 2: Trading (7 rounds)</td></tr>
<tr><td>…</td><td>…</td></tr>
<tr><td rowspan="2">Market 20</td><td>Stage 1: Payment choice</td></tr>
<tr><td>Stage 2: Trading (7 rounds)</td></tr>
</table>

More Information for Sellers

As a seller, your earnings in a market (in EM) are calculated as

Option I	Accept payment 2	Number of payment 1 transactions x 0.5 + **Number of payment 2 transactions x 0.9 – 2.8**
Option II	Not accept payment 2	Number of payment 1 transactions x 0.5

The benefit to sellers of accepting payment 2 is to increase the likelihood that you sell goods to buyers (remember no trade can take place if the buyer has only payment 2 and you do not accept it), and to reduce transaction costs and therefore increase net earnings by 0.4 EM each time a buyer pays in payment 2. The cost to sellers of accepting payment 2 is that you have to pay a one-time fee of 2.8 EM at the beginning of the market even if no buyers offer to pay you with payment 2 in that market.

Which option leads to higher earnings depends on all other 13 subjects' decisions. Table 1 on page 7 lists the average market earnings for the seller from the two options (accept / reject payment 2) in cases where all buyers choose to allocate between 0~7 EM to payment 2, and where 0~6 of the other 6 sellers choose to accept payment 2. As you can see, either option can give higher earnings depending on other participants' decisions. During the experiment, please keep Table 1 at hand for reference. In addition, you can use a "what if" calculator on the computer screen to compute the average earnings in situations where buyers make different payment allocations.

Your earnings from accepting payment 2 tend to increase if more buyers allocate more money to payment 2, and if fewer sellers accept payment 2. The opposite is true if you reject payment 2.

More Information for Buyers

As a buyer, your earnings in a market are calculated as

Number of payment 1 transactions x 0.5 + Number of payment 2 transactions x 0.9

As a buyer, the benefit of allocating more money to payment 2 is that you save 0.4 EM each time you use payment 2 instead of payment 1. The cost is the risk that you may not be able to trade if the seller does not accept payment 2 and you run out of payment 1 (which is always accepted). Your market earnings depend on your own payment allocation and the 7 sellers' decisions on acceptance of payment 2. Table 2 on page 7 lists the buyer's market earnings if the buyer allocates 0~7 EM to payment 2 (and the rest to payment 1) and if 0~7 sellers accept payment 2. You should allocate more money to payment 2 if you expect more sellers to accept it. Table 2 will also be on your computer screen when you make payment decisions.

Forecast

At the start of each market before making payment decisions, you are asked to forecast other participants' choices for that market. Buyers forecast how many of the 7 sellers will choose to accept payment 2. Sellers forecast (1) the average amount of EM that all 7 buyers will allocate to payment 2, and (2) how many of the other 6 sellers will accept payment 2. You earn 0.5 EM per correct forecast in addition to your earnings from buying/selling goods.

Earnings

At the end of the experiment, you will be paid your earnings in cash and in private. Your earnings in dollars will be: Total earning (trading + forecasting) in EM x 0.15 + 7 (show-up fee).

Computer Interface

You will interact anonymously with other participants using the computer workstations. You will see three types of screens (Figures 1-6 show sample screens).

Payment choice screen, Figures 1-2. This is where you make payment choices depending on whether you are a buyer (Figure 1) or a seller (Figure 2). Each screen has 4 parts. The upper portion summarizes information about previous markets. To the left of the blank column are your own activities, including your payment choice, the number of transactions using each of the two payment methods, the number of no-trade meetings, market earning from trading, and the number of correct forecasts that you made. To the right of the blank column, there is an aggregate market-level statistic, the number of sellers who accepted payment 2.

The middle section provides information about your average potential earnings from trading in each market. The buyer screen (Figure 1) shows Table 2. The seller screen (Figure 2) has a "what if" calculator. A seller can type in the number of buyers choosing to allocate 0~7 EM to payment 2 and the number of other 6 sellers accepting payment 2 (the default value is 0 in all fields; the first 8 fields must add up to 7; enter an integer 0~6 in the last field), press the "Calculate" button to create a record showing the average market earnings from accepting payment 2 and not accepting it, as well as the average buyers' allocation to payment 2 in that scenario. For example, if you would like to check your potential average earnings in the situation where **5** buyers allocate 2 EM to payment 2, **2** buyers allocate 3 EM, and **3** of the other six sellers accept payment 2, type in "**5**" in the field "# buyers with pay2=2", "**2**" in the field "# buyers with pay2=3", and "**3**" in the field "# other sellers accept pay2." You can create as many records as you wish at the start of each market.

In the lower-left section, you forecast what other participants will do in the new market. Enter an integer within the indicated range for each forecast. The seller's forecast of buyer's average payment 2 allocation is counted as correct if it lies within ±1 of the realized value.

In the lower-right section, you choose how to split your 7 EM between the two payment methods if you are a buyer (Figure 1), and whether to accept payment 2 at a one-time fee of 2.8 EM if you are a seller (Figure 2).

Trading screen, Figures 3-4**.** In each of the 7 trading rounds, buyers decide whether to buy a unit of the seller's good using either payment 1 or payment 2. This decision depends on the buyer's remaining balances of payment 1 and payment 2, and whether or not the seller has agreed to accept payment 2; this information is shown on the buyer's computer screen (see the lower left box in Figure 3). Sellers do not choose at this stage, and can click on the "OK" button to review information on the waiting screen (see Figure 4). From round 2 on, the upper section of the screen reviews your activities in the previous round and in the current market up until then.

Waiting screen, Figures 5-6. At any point in the experiment if you finish your decision sooner than other participants, you will see a waiting screen with information on previous markets and your potential market earnings similar to what you observe on the payment choice screen.

Finally, sellers who invest in the one-time fixed cost to accept payment 2 may have a negative "market earnings" in one or a few rounds. As a result of this, you may see a message screen explaining the situation. After you have been alerted to this situation, you can click on the "continue" button on the screen to proceed.

Figure 1: Buyer's payment allocation screen

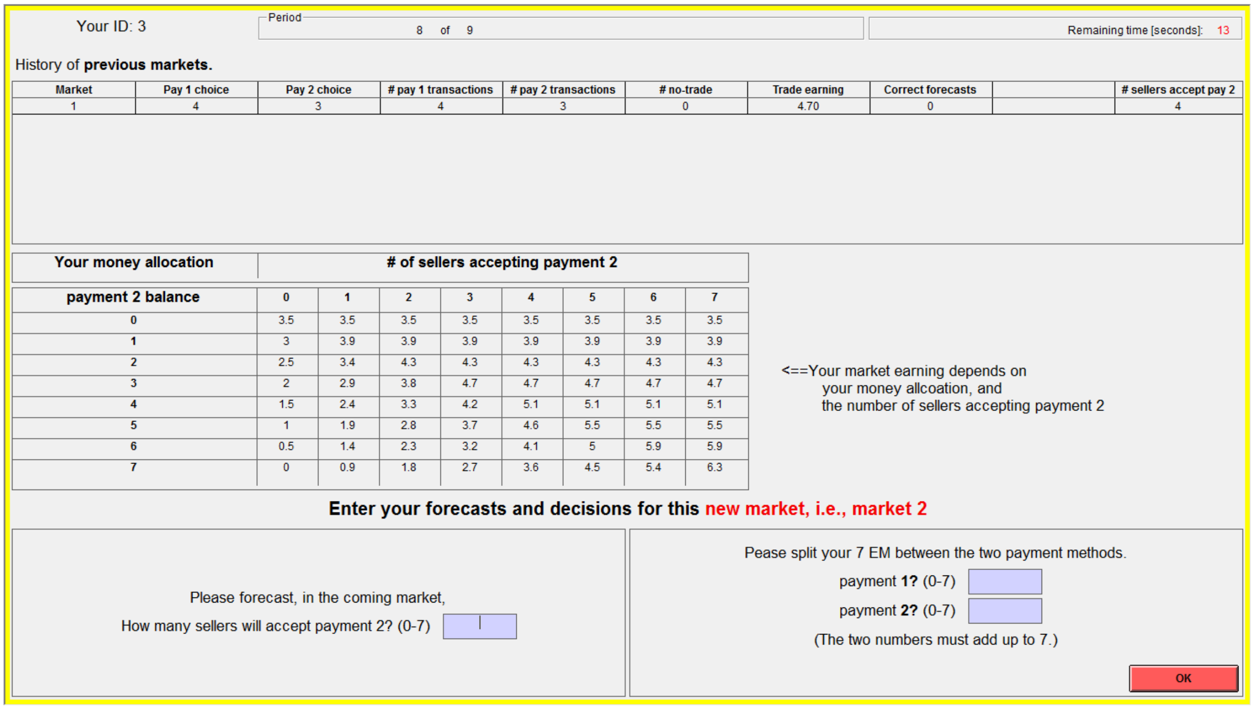


Figure 2: Seller's payment 2 acceptance screen

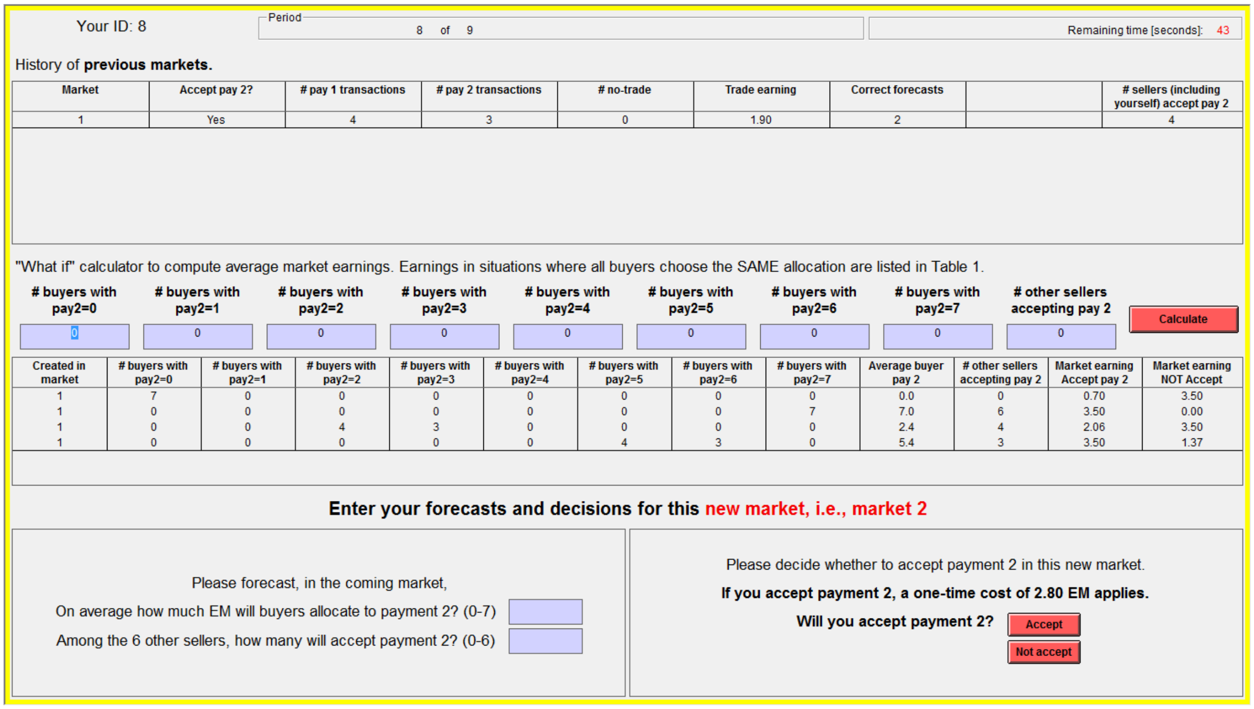


Figure 3: Buyer's trading screen

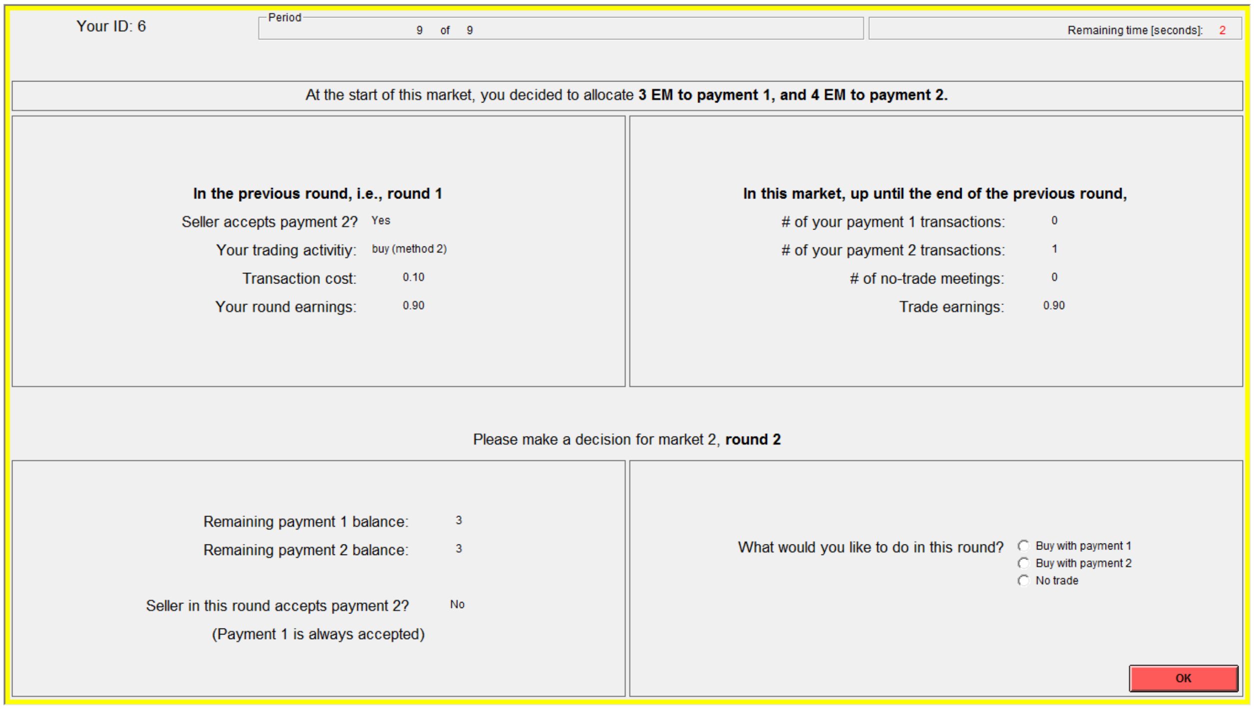


Figure 4: Seller's trading screen

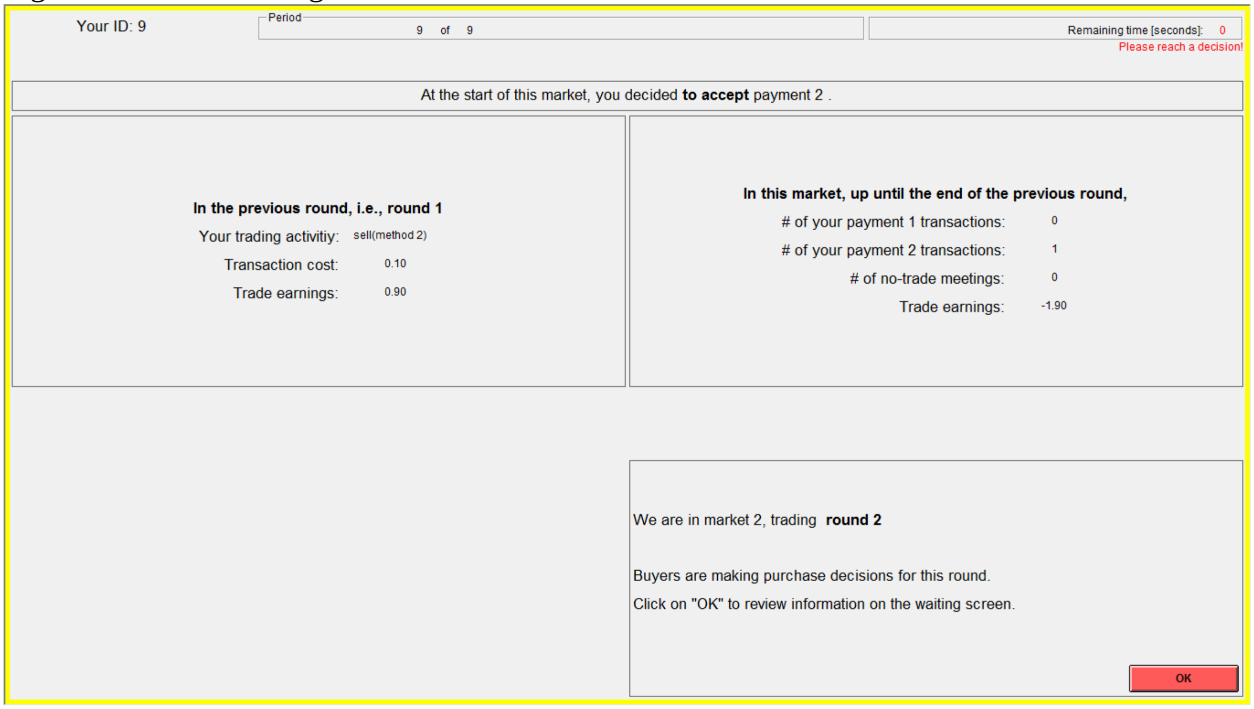
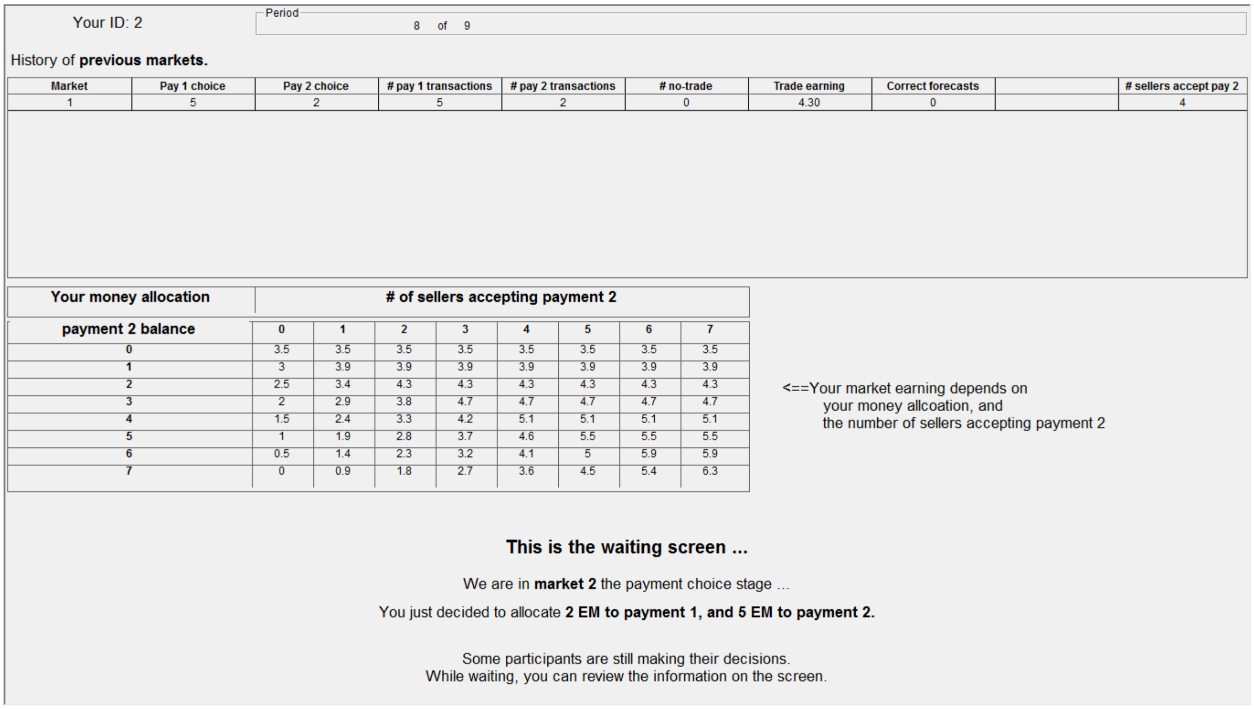


Figure 5: Buyer’s waiting/information screen



Your ID: 2

Period 8 of 9

History of **previous markets.**

Market	Pay 1 choice	Pay 2 choice	# pay 1 transactions	# pay 2 transactions	# no-trade	Trade earning	Correct forecasts		# sellers accept pay 2
1	5	2	5	2	0	4.30	0		4

Your money allocation	**# of sellers accepting payment 2**							
payment 2 balance	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
0	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5
1	3	3.9	3.9	3.9	3.9	3.9	3.9	3.9
2	2.5	3.4	4.3	4.3	4.3	4.3	4.3	4.3
3	2	2.9	3.8	4.7	4.7	4.7	4.7	4.7
4	1.5	2.4	3.3	4.2	5.1	5.1	5.1	5.1
5	1	1.9	2.8	3.7	4.6	5.5	5.5	5.5
6	0.5	1.4	2.3	3.2	4.1	5	5.9	5.9
7	0	0.9	1.8	2.7	3.6	4.5	5.4	6.3

<==Your market earning depends on
your money allcoation, and
the number of sellers accepting payment 2

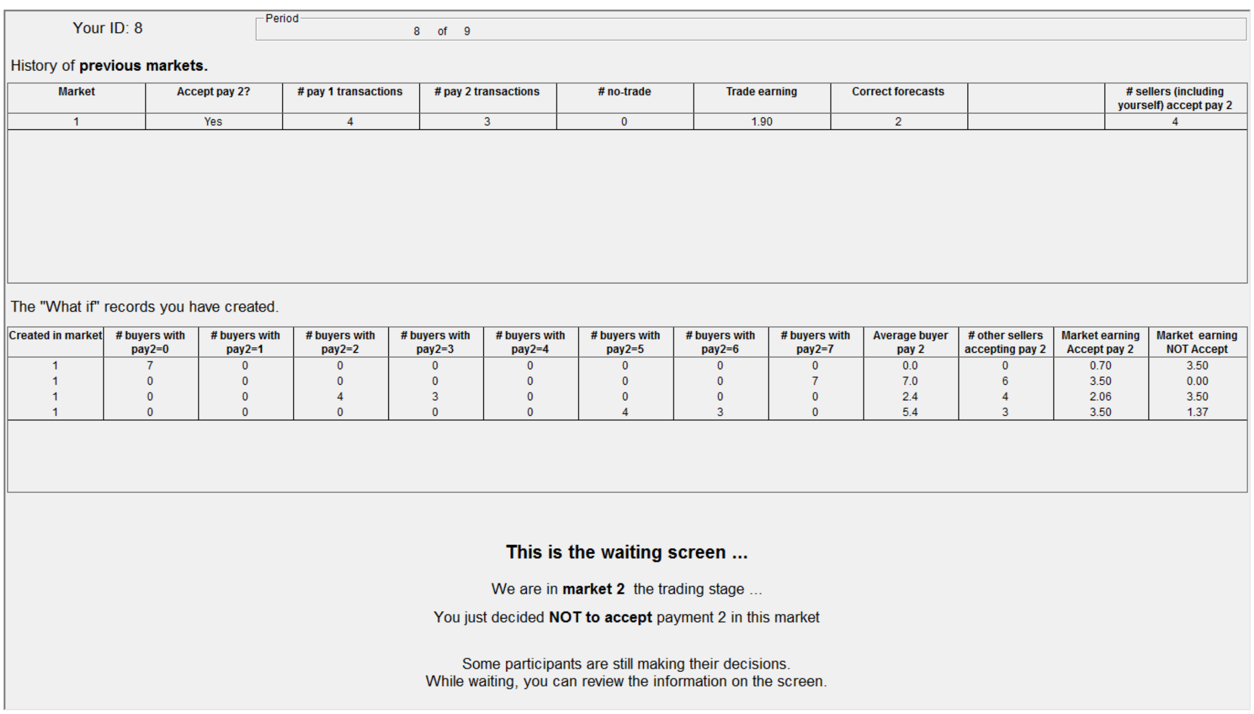
This is the waiting screen ...

We are in **market 2** the payment choice stage ...

You just decided to allocate **2 EM to payment 1, and 5 EM to payment 2.**

Some participants are still making their decisions.
While waiting, you can review the information on the screen.

Figure 6: Seller’s waiting/information screen



Your ID: 8

Period 8 of 9

History of **previous markets.**

Market	Accept pay 2?	# pay 1 transactions	# pay 2 transactions	# no-trade	Trade earning	Correct forecasts		# sellers (including yourself) accept pay 2
1	Yes	4	3	0	1.90	2		4

The "What if" records you have created.

Created in market	# buyers with pay2=0	# buyers with pay2=1	# buyers with pay2=2	# buyers with pay2=3	# buyers with pay2=4	# buyers with pay2=5	# buyers with pay2=6	# buyers with pay2=7	Average buyer pay 2	# other sellers accepting pay 2	Market earning Accept pay 2	Market earning NOT Accept
1	7	0	0	0	0	0	0	0	0.0	0	0.70	3.50
1	0	0	0	0	0	0	0	7	7.0	6	3.50	0.00
1	0	0	4	3	0	0	0	0	2.4	4	2.06	3.50
1	0	0	0	0	0	4	3	0	5.4	3	3.50	1.37

This is the waiting screen ...

We are in **market 2** the trading stage ...

You just decided **NOT to accept** payment 2 in this market

Some participants are still making their decisions.
While waiting, you can review the information on the screen.

Table 1: Seller's average market earnings

- This table considers the case where ***all buyers choose the same payment allocation;*** use the "what-if" calculator for cases where buyers make different allocations.
- The earnings for ***accep****ting* payment 2 are in the ***upper-left*** corner,
- The earnings for ***not accep****ting* payment 2 are in the ***lower-right*** corner.

All buyer's allocation to **payment 2**	# of **other 6 sellers** accepting payment 2							
	0	1	2	3	4	5	6	
0	0.7 3.5	0.7 3.5	0.7 3.5	0.7 3.5	0.7 3.5	0.7 3.5	0.7 3.5	←if accept pay 2 ←if not accept pay 2
1	3.5 3.0	2.1 3.5	1.6 3.5	1.4 3.5	1.3 3.5	1.2 3.5	1.1 3.5	
2	3.5 2.5	3.5 2.9	2.6 3.5	2.1 3.5	1.8 3.5	1.6 3.5	1.5 3.5	
3	3.5 2.0	3.5 2.3	3.5 2.8	2.8 3.5	2.4 3.5	2.1 3.5	1.9 3.5	
4	3.5 1.5	3.5 1.8	3.5 2.1	3.5 2.6	2.9 3.5	2.6 3.5	2.3 3.5	
5	3.5 1.0	3.5 1.2	3.5 1.4	3.5 1.8	3.5 2.3	3.0 3.5	2.7 3.5	
6	3.5 0.5	3.5 0.6	3.5 0.7	3.5 0.9	3.5 1.2	3.5 1.8	3.1 3.5	
7	3.5 0	3.5 0	3.5 0	3.5 0	3.5 0	3.5 0	3.5 0	

Table 2: Buyer's market earning

Your allocation to **payment 2**	# of sellers accepting payment 2							
	0	1	2	3	4	5	6	7
0	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5
1	3.0	3.9	3.9	3.9	3.9	3.9	3.9	3.9
2	2.5	3.4	4.3	4.3	4.3	4.3	4.3	4.3
3	2.0	2.9	3.8	4.7	4.7	4.7	4.7	4.7
4	1.5	2.4	3.3	4.2	5.1	5.1	5.1	5.1
5	1.0	1.9	2.8	3.7	4.6	5.5	5.5	5.5
6	0.5	1.4	2.3	3.2	4.1	5.0	5.9	5.9
7	0.0	0.9	1.8	2.7	3.6	4.5	5.4	6.3