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UNIVERSITY OF CALIFORNIA SANTA CRUZ

ESSAYS ON THE THEORY OF MONEY AND MONETARY POLICY

A dissertation submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Justin D. Rietz

September 2016

The Dissertation of Justin D. Rietz is approved:

Professor Daniel Friedman, Chair

Professor Carl Walsh

Professor Kenneth Kletzer

Tyrus Miller Vice Provost and Dean of Graduate Studies Copyright © by

Justin D. Rietz

2016

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Abstract

Essays on the Theory of Money and Monetary Policy

by

Justin D. Rietz

In the first chapter, I examine in a controlled, experimental laboratory setting, the acceptance of a secondary currency when a primary currency already circulates in an economy. The underlying model is an indivisible good / indivisible money, dual currency search model similar to that in Kiyotaki and Wright (1993) and Craig and Waller (2000). In such models, there are two pure Nash equilibria - total acceptance or total rejection of the secondary currency - and one unstable, mixed equilibrium denoted as partial acceptance. This mixed equilibrium is considered an artifact of the indivisibility of money and goods in the model and is often ignored. I find that when barter between good holders is allowed, the equilibrium tends towards total rejection. Conversely, when barter is prohibited, the equilibrium tends towards total acceptance. However, in both cases, the economies as a whole display partial acceptance of the secondary currency.

In the second chapter, I continue this exploration of secondary currency acceptance using agent-based models. In particular, the models employ genetic algorithms for agent learning. The results in many ways coincide with those of the laboratory experiments, though under certain parameter settings, the economies simulated in the agentbased models often converge to complete acceptance or rejection of the secondary currency.

In the third chapter, I change focus and examine the impact of foreign government purchases of U.S. Treasury securities on U.S. interest rates. While several past studies have considered the impact of such flows on U.S. long-term interest rates, few, if any, have simultaneously included Federal Reserve purchases of Treasury securities. Therefore, I undertake an empirical analysis that includes both types of purchases, particularly relevant given the Fed's recent large-scale asset purchase program, and have included updated data through April 2014. I find that both foreign government and Federal Reserve Treasury purchases had a significant impact on medium and long-term yields. To my family,

Ivelina, Alexandra, and Liam,

whose support, patience, and love made this possible.

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This list is far from complete, and apologies in advance to those I have not included but surely not forgotten.

Part I

Secondary Currency Experiments

Chapter 1

Secondary Currency Acceptance: Experimental Evidence with a Dual Currency Search Model

1.1 Introduction

"[Bitcoin] has to have intrinsic value. You have to really stretch your imagination to infer what the intrinsic value of Bitcoin is. I havent been able to do it. Maybe somebody else can." - Alan Greenspan, Bloomberg, December 2013

The recent advent of decentralized, virtual or cryptocurrencies, such as Bitcoin, has

raised many questions as to their possible impacts on traditional payment systems and the financial system in general. Underlying these questions is the fundamental concept of what defines money and what drives demand and acceptance of a medium of exchange. Modern monies evolved historically from commodity-backed monies into fiat monies, i.e. token¹ monies backed by government decree. Cryptocurrencies, essentially intangible electronic bits on a computer with no legal backing, complicate the issue as they are token money yet are not legal tender "for all debts, public and private." This begs the question as to why individuals and businesses are willing to accept such a secondary currency in exchange for goods and services given that generally-accepted fiat currencies already circulate in most, if not all, countries.

1.1.1 Secondary Currency History and Examples

In his 1933 book "Stamp Scrip", Irving Fisher claimed that in the face of a U.S. dollar shortage, presumably the result of hoarding, the introduction of a secondary currency might "prime the pump" of credit currency use and thus begin the end to the Great Depression. Fisher was particularly interested in stamp scrip which consisted primarily of private or community-issued token money that required the regular affixation of a marginally priced stamp that could be purchased from the issuer. This tax on currency use was intended to increase the velocity of money and thus spur business transactions

¹I will generically refer to money with exchange value significantly above its component value as "token", and will refer to money backed by government decree as fiat money.

and economic growth. While he cautioned that stamp scrip was no panacea, Fisher strongly believed that the use of a secondary currency would help overcome the shortage of fiat money during the Great Depression and the inability of barter to efficiently enable economic transactions.

Economic crises are often the genesis of secondary currencies that circulate along side, or in lieu of, a national fiat currency. During the severe recession in Argentina in 2002, individuals created local business associations that issued private currencies called "creditos" that circulated not only between members of an association, but also between different associations (Colacelli and Blackburn 2009). A similar phenomena occurred in Greece during its recent debt crisis when privately issued "TEMS" were used in lieu of Euros in response to wage cuts and unemployment (Donadio 2011). Even earlier in history, during small change shortages in Great Britain during the 1700s, privately minted coins circulated at values above that of their metallic content (Selgin 2008). Hyperinflations have also led to the endogenous adoption of foreign currencies, a recent example being the use of U.S. dollars and South African rand, among other foreign currencies, in Zimbabwe (Polgreen 2012).

However, not all secondary or multi- currency systems have been born of economic turmoil. In Scotland during the 18th century and the U.S. during the 19th century, a "free banking" system existed in which banks issued private notes, most often backed back by silver or gold. More recent examples include community currencies such as the Ithaca dollar in New York and BerkShares in Berkshire, Massachusetts. Internationally, currencies of neighboring countries are often accepted at par in border cities, a phenomena seen along the Canada - Minnesota border that has also spread to nonborder states.².

In all of the above examples, individuals accept token money in exchange for goods or services rather than demand an existing fiat currency locally in circulation. Presumably this is done under the assumption that the token money would in turn be accepted in future exchange. While economists have developed multiple models to describe this phenomena - money search models being the most recent and arguably most often used - these models often make fundamental assumptions regarding agent choices that are not necessarily founded in actual human behavior. Particularly, early money search models such as Kiyotaki and Wright (1993) assumed agents would rationally optimize profits over a range of currency acceptance rates. More recent search models, such as those found in Trejos and Wright (1995, 1996) and Craig and Waller (2000) assume either "take it or leave it" offers by buyers or some form of Nash bargaining.

Controlled laboratory experiments with human subjects provide a systematic and methodological-based mechanism with which to test these behavioral assumptions. Though several researchers have conducted experiments testing the predictions and dynamics of single token and fiat currency money search models, I am not aware of any

²While Canadian bank notes are typically not accepted in Minnesota, coins are, perhaps due to the visual similarity of Canadian and U.S. coinage and their relatively small exchange value.

experimental research (with the possible exception of preliminary work undertaken by Janet Hua Jiang of the Bank of Canada and Cathy Zhang at Purdue University) that has specifically looked at economies with two token currencies, one of which is a priori generally accepted and another which is not. Therefore, I specifically address in my research the behavior of individuals in a dual currency economy in which a primary currency is by design generally accepted in exchange - and thus acts to a certain extent as a national fiat currency - and a secondary currency which individuals may decide to accept or reject in exchange for goods. Moreover, as the key friction addressed by money search models is the existence or absence of a double coincidence of wants, I compare two environments, one in which sellers may barter, and one in which they may not.

The structure of this paper is as follows. In Section 2, I will review the relevant literature, covering both theoretical models of secondary currency economies and related experimental work. In Section 3 I will describe in detail the underlying models upon which I based my laboratory experiments. Experimental procedures and design are discussed in Sections 4 and 5, respectively. This is followed by the experimental results in Section 6, and the conclusion.

1.2 Literature Review

Duffy (2008) succinctly breaks down much of the experimental work in monetary economics into two categories: money as a store of value and money as a medium of exchange.³ Experiments based on search models all fall within the medium of exchange category, while experiments based on cash-in-advance ("CIA") and overlapping generations models ("OLG") predominantly fall into the store of value category. While some experiments have studied the emergence of money from the trade of different commodities (Duffy and Ochs 1999), others have focused on the impact of the introduction of a fiat money (Duffy and Ochs 2002, Deck et al 2006). However, few, if any, studies have explicitly considered multiple fiat monies, with the exception of the open, general equilibrium economy in Noussair et al (2007) and Angerer et al (2010).

Brown (1996) and Duffy and Ochs (1999) are examples of earlier experimental research examining the 1st generation money search models that focus on commodity monies. The underlying model consists of three types of agents identified by the good they consume, $i = \{1, 2, 3\}$. However, type 1 produces good 2, type 2 produces good 3, and type 3 produces good 1. Hence, no double coincidence of wants naturally occurs. Each good has a different storage cost c, with $c_1 < c_2 < c_3$. Agents are randomly matched, and may trade their goods if mutually agreeable. If an agent trades for its

³I have not included experimental work on New Keynesian models, specifically money illusion, for reasons of relevance and brevity.

consumption good, it consumes the good, gains utility, and then immediately produces its production good. In the above parameterization, type 2 should be willing to trade type 3 for good 1, good 1 having a lower storage cost, and in turn trade this for its consumption good in a match with a type 1 player. Thus, agents play a fundamental strategy in which they try to hold only the lowest cost good which becomes the de facto medium of exchange.

Duffy and Ochs (1999) utilized participant groups which consisted of a minimum of 2 players of each type (i.e. a minimum of N = 6), with equal numbers of each type, interacting in a computerized environment. Each session consisted of multiple games which in turn consisted of multiple rounds. At the beginning of a game, subjects were given an initial endowment of utility points. In a round, subjects were randomly matched and could trade goods and gain utility points by trading for and consuming their preferred good. A cost (in terms of utility points) was incurred to store a good until the next round. Another round occurred with a probability of 90%; otherwise, the game ended, subjects' points were recorded and reset, and a new game began. This indirectly induced a 10% discount rate. Subjects, via the computer display, were able to see the round number, their point totals, the fraction of each type of player that held each type of good, and the probability of the game coming to an end. This information is considered common knowledge in the Kiyotaki and Wright (1989) framework.

In accordance with the underlying theory, in the standard parameterization de-

scribed above, the type 1 (lowest storage cost) good was used as a medium of exchange and subjects almost always played this fundamental strategy. However, the researchers also tested a different set of parameterizations under which there is also a speculative strategy in which type 1 agents should trade their good to type 2 agents in exchange for good 3 (which has a higher storage cost) in order to trade for their consumption good with type 3 agents. In both Duffy and Ochs (1999) and Duffy and Ochs (2002), subjects played the speculative strategy much less often than predicted. In an effort to evoke this strategy, the experimenters split the population unequally among the three types of players (i.e. 4/9 of the population were type 3 players) to make it more advantageous to speculate for the type 3 good. This, along with automating type 2 and type 3 players' decisions, improved the theoretical match, though the fundamental strategy was still played more often than predicted.

Subsequent experimental research considers the introduction of fiat money into an artificial economy. Duffy and Ochs (2002) follow the setup of their earlier 1999 work (3 types of players, 3 commodities with different storage costs, multiple games consisting of multiple rounds) but introduce a fourth good ("good 0") that has neither consumption value nor a storage cost. A fraction m of the population initially has good 0 in storage at the beginning of a game, and as good 0 is not consumed, this fraction is constant during a given game. Subjects' types are consistent throughout the session (i.e. they don't change between games), but at the beginning of each game, the initial endowment

of money is randomized among types. The computerized environment again provided subjects with information on historical averages (within a game) as to which types of players held which type of goods. As theory suggests, good 0 was used as a medium of exchange as long as it had the lowest storage cost (i.e. was not dominated in rate of return), and was used much less frequently when it was costlier to store than at least one of the other goods.

Recent experimental research by Duffy and Puzzello (2014) tests a third generation search model similar to that of Lagos and Wright (2005) and Rocheteau and Wright (2005) in which both money and goods are divisible, and there are two sub-rounds. In a similar setup to Duffy and Ochs (2002) the first subround consisted of decentralized, random matching in which buyers could make take-it-or-leave it offers to sellers. The second subround consisted of a centralized, double auction market in which subjects could choose to either buy or sell goods⁴. The authors compare the results of this standard setup to an experiment in which subjects are not endowed with money, i.e. a gift economy. In this case, in the decentralized match, buyers request goods from sellers, and sellers provide goods presumably on the implicit promise that when the roles are reversed, the then sellers will reciprocate. Results in the money economy came close to, but were still below, the predicted efficient outcomes. However, in the gift economy, trade was significantly below that of predictions, suggesting that money

⁴This second subround is in line with the theory in third generation search models, as it is needed (along with quasi-linear utility functions) in order to get tractable results, specifically to ensure that agents enter the decentralized subround with equal money holdings.

plays a crucial role in coordinating exchange, particular as a memory mechanism.

Deck et al (2006) undertake an experiment to determine when the acceptability of a fiat money will collapse. Subjects were assigned one of three roles: type A or B who both consume and produce, or the role of a government, type G. In the first two experiments, types A and B were endowed with goods and tickets, and each consumed the others production good. As the basis for the experiment was a CIA model, direct barter was not allowed and subjects had to use tickets to exchange for goods in a double auction market. The authors tested scenarios in which payouts were 1) earned for both consumption and tickets holdings (commodity money), and 2) only for consumption (fiat money). In both cases, equilibrium prices and quantities were near the efficient levels predicted by the underlying model, though when the number of trading rounds in the fiat money scenario were reduced, prices tended to escalate above those predicted. In contrast, when a government capable of printing tickets and buying goods was introduced, prices quickly escalated and the resulting hyperinflation reached upwards of 2000% between trading periods. Hyperinflation was mitigated, however, when an exogenous money supply growth rule was put in place. In a similar experiment, Deck (2004) shows that when the government must follow a balanced budget rule, hyperinflation was also avoided.

As mentioned in the introduction to this section, the number of experimental studies on multiple fiat currencies is limited. Of note are Noussair et al (2007) and Angerer et al (2010). Noussair and co-authors Plott and Riezman modeled a large, multi-country economy in a general equilibrium setting in which there were three countries, each with its own currency; three types of traded goods; two non-tradeable inputs, labor and capital; and three types of agent roles: suppliers, producers, and consumers. Subjects in the experiment were assigned a nationality and played two roles, though they never produced a good they consumed. All goods and currencies were traded in centralized, double auction markets.⁵. In order to consume a good produced in another country, the good had to be imported, and in order to import a good, a subject had to first exchange her local currency for a foreign currency in the appropriate forex market. Strikingly, the quantities and prices traded in all markets ultimately converged quite closely to the theoretical predictions. However, as only one currency could circulate within a given country, the possibility of within borders, competing fiat currencies was not considered.

Angerer et al (2010) conduct an experiment in which participants issued "IOUs" that they could costlessly trade in a centralized clearinghouse. Subjects were endowed with 200 units of either good A or good B, and could issue up to 6000 IOUs. Utility was maximized by consuming 100 units of each good, though subjects could not consume their endowments. All units were placed for sale in a clearinghouse, and subjects bid on each good. The computerized clearinghouse determined the market clearing price and quantities, and all subjects received the same quantities. Each game consisted of

⁵Understandably, this experiment is considered one of the most complex economies to be taken to the laboratory.

15 rounds of this process. The results for this baseline game were consistent with noncooperative utility maximization, though the prices subjects offered for their own good were lower than expected. In a second treatment, the experiment allowed subjects to renege on their promises, i.e. after the clearinghouse bidding process, subjects did not need to deliver all 200 units. The resulting total units delivered were then distributed equally among subjects, and any withheld goods were counted towards that subject's consumption. In this treatment, delivery dropped considerably, averaging about 50 units out of subjects' 200 unit endowments. However, when a high enough non-delivery penalty was put in place, near-total delivery occurred.

1.3 Theoretical Background and Model

My experiment consists of two related goals: 1) to test the theoretical predictions of a dual currency search model in a controlled experimental setting, and 2) to determine whether or not the existence of barter impacts the acceptance of a secondary currency. The baseline model is a first generation, indivisible goods / indivisible money search model based on Kiyotaki and Wright (1993) that allows for barter, i.e. exchange between two good holders.

In the model, there are two currencies, primary and secondary, and nonperishable goods. Agents may be good holders, primary currency holders, or secondary currency holders with population proportions μ_g , μ_p , and μ_s , respectively, and $\mu_g + \mu_p + \mu_s = 1$.

Each agent receives utility U from the consumption of a fraction x of goods but may never consume the good it holds. When an agent holding a good meets an agent holding one of the two currencies, a single coincidence of wants occurs with probability x and with symmetry, a double coincidence of wants occurs with probability x^2 when two agents holding goods meet. It is costless to store money and commodities, though there are currency-specific dividend returns y_i . The rate of time preferences is r.

Agents are randomly matched for bilateral trade with probability α . If an agent holding one of the currencies meets an agent holding a good, there is a possibility of trade. If trade does occur, the agent holding the currency receives the good, consumes it and earns utility *U*. This agent then produces a new good which the agent may trade in future matches. The agent that trades its good for the currency carries that currency into its next trading match.

An agent holding a good optimally accepts the primary or secondary currency with probability π_p and π_s (best responses), respectively. Agents holding a currency take the probabilities of an agent holding a good accepting either currency as given, and therefore these probabilities in the currency holder Bellman equations are denoted as Π_p and Π_s . Currency for currency trades are not allowed for the purposes of clarity, but including such trades does not affect the equilibrium results.

Let V_i represent the value function for agent *i*, where i = g, p, s indicates that the agent is a good holder, primary currency holder, or secondary currency holder, respec-

tively. The Bellman's equations are therefore:

$$rV_g = \alpha \mu_g x^2 (U - V_g) + \alpha \mu_p x \max_{\pi_p} \pi_p (V_p - V_g) + \alpha \mu_s x \max_{\pi_s} \pi_s (V_s - V_g)$$
(1.1)

$$rV_p = y_p + \alpha \mu_g x \Pi_p (U + V_g - V_p)$$
(1.2)

$$rV_s = y_s + \alpha \mu_g x \Pi_s (U + V_g - V_s) \tag{1.3}$$

Equation (1.1) is the flow return to an agent holding a good. This return consists of three components. The first component of the right-hand side of the equation is the benefit from trading with another agent holding a good. This occurs with probability $\alpha \mu_g x^2$. The second component is the benefit from trading with a primary currency holder, which occurs with probability $\alpha \mu_p x$, assuming the agent holding the good decides to trade. The third component is the benefit from trading with a secondary currency holder, which occurs with probability $\alpha \mu_s x$, again assuming the agent holding the good decides to trade.

Equation (1.2) is the flow return to an agent for holding the primary currency. As currency trade is not allowed, the return consists of a dividend paid (or cost incurred) for holding the primary currency y_p plus the utility gain from trading with a good holder which occurs with probability $\alpha \mu_g x \Pi_p$, with Π_p taken as given by the agent holding the primary currency holder. Likewise, Equation (1.3) is the flow return to an agent for holding the secondary currency.

In order to motivate a secondary currency scenario in which the secondary currency circulates with partial acceptance, I follow Kiyotaki and Wright (1993) and assume that

the primary currency is always accepted in trade: $\Pi_p = 1$. Therefore, $\Pi_p = 1 > \Pi_s > 0$ meaning that $V_p > V_s = V_g$. That is, the value of holding the primary currency is higher than the value of holding the secondary currency or a good, and agents are indifferent between holding the secondary currency and a good. For simplicity, dividend returns to currency are set to zero. Solving for Π_s yields:

$$\Pi_{s} = \left(\frac{xr + x^{2}\alpha\mu_{g} + x\alpha\mu_{p}}{r + x\alpha(\mu_{g} + \mu_{p})}\right)$$
(1.4)

This is the mixed strategy equilibrium. Therefore, there are three equilibria: partial acceptance of the secondary currency, total acceptance of the secondary currency, and total rejection of the secondary currency. It is important to note that it is often implicitly assumed that the agent-level symmetric mixed equilibrium is the same as an asymmetric equilibrium in which a fraction of the population of agents always accepts the secondary currency and a fraction does not. As Wright (1999) shows, this is not necessarily the case.

Moreover, this mixed strategy equilibrium is evolutionarily unstable. Starting at the mixed equilibrium Π_s^* , a slight increase in the fraction of agents accepting the secondary currency, Π_s will cause an explosion to the full acceptance equilibrium. Likewise, a small decrease in Π_s will cause a degeneration to the full rejection equilibrium. This is displayed stylistically in Figure 1.1. It is this evolutionary process I explore in the experimentally laboratory setting.

Figure 1.1: Evolutionary Dynamics of Secondary Currency Acceptance



The model for the no barter treatment is similar to the model above but more closely follows Colacelli and Blackburn (2009) in their field research on creditos systems in Argentina. Repeating value equations (2) and (3) from above and using the same notation, the model is:

$$rV_g = \alpha \mu_p x \max_{\pi_p} \pi_p (V_p - V_g) + \alpha \mu_s x \max_{\pi_s} \pi_s (V_s - V_g)$$
(1.5)

$$rV_p = \alpha \mu_g x \Pi_p (U + V_g - V_p) \tag{1.6}$$

$$rV_s = \alpha \mu_g x \Pi_s (U + V_g - V_s) \tag{1.7}$$

Equation (1.5) is the return to an agent for holding a good which consists of only two components versus three as barter is not allowed. The first component of the righthand side of the equation is the benefit from trading with a primary currency holder, which occurs with probability $\alpha \mu_p x$ assuming the agent holding the good does decide to trade. The second component is the benefit from trading with a secondary currency holder, which occurs with probability $\alpha \mu_s x$, again assuming the agent holding the good decides to trade.

Setting $\pi_p = \Pi_p = 1$ to indicate that the primary currency is always accepted and noting that $\pi_s = \Pi_s$ in equilibrium, a mixed strategy equilibrium for secondary currency

acceptance exists when

$$\Pi_s = \frac{x \alpha \mu_p}{r + x \alpha (\mu_g + \mu_p)} \tag{1.8}$$

Comparing the barter to no barter equilibria:

$$\Pi_{s,barter} = \frac{xr + x^2 \alpha \mu_g + x \alpha \mu_p}{r + x \alpha (\mu_g + \mu_p)} > \frac{x \alpha \mu_p}{r + x \alpha (\mu_g + \mu_p)} = \Pi_{s,nobarter}$$
(1.9)

The mixed equilibrium, which is an unstable source in the evolutionary sense, is higher in the barter economy than in the no-barter economy. Therefore, in order for a secondary currency to circulate in a given economy, ceteris paribus, the fraction of good holders that accept the secondary currency in an economy in which double coincidence of wants (barter) may occur must be higher than the fraction of good holders that accept the secondary currency in an economy with only single coincidence of wants (no barter) may occur. This suggests that a secondary currency is more likely to circulate in an economy with no barter versus in an economy in which barter may occur. Intuitively, the value of holding a good in a no barter economy is less than in a barter economy as a good cannot be used to exchange for an item from which an agent directly gains utility. Likewise, the relative value of the secondary currency increases in the no barter economy as currency is a prerequisite for trade.

1.4 Experimental Procedures

The subject pool consisted of University of California Santa Cruz undergraduate students, and subjects only participated in one session consisting of one treatment. Sixteen subjects were recruited for each session plus six extras. Subjects had no prior experience with the experiment and participation was voluntary. The experiment was computerized using zTree software (Fischbacher 2007) on a Linux platform and was run in the Learning and Experimental Economics Projects at UC Santa Cruz.

At the beginning of each experimental session, subjects were provided with written instructions (see "Supplementary Materials" for copies of the instructions). After the instructions were read, subjects used their computer workstations to answer multiple questions (also available in "Supplementary Materials") to test their knowledge of the experiment.⁶ Once all subjects successfully completed the quiz, they played four practice rounds to ensure they understood the rules and the computer interface.

Four sessions of each treatment (barter and no barter) were run for a total of eight sessions. Sessions typically took between 45 minutes to one hour. During the session, subjects were not allowed to communicate with each other or use cell phones, tablets, laptops, or other electronic devices. At the end of the session, subjects were given their cash payout consisting of a \$7.00 showup fee plus a performance component depen-

⁶During pilot testing sessions of the experiment, subjects were given the opportunity to provide written feedback on the instructions. The large majority of the feedback indicated that the instructions were clear and understandable.

dent on their actions during the experiment. When sessions were overbooked, sixteen subjects from the total number of subjects that showed up were randomly selected to participated in the session. Those who were turned away still received the \$7.00 showup fee. See Table 1.1 for details on the sessions and payouts.

Session	Treatment ¹	Sequences	Periods	Total Payout ²	Avg. Payout
1	В	9	108	\$225.25	\$14.07
2	В	13	101	\$224.75	\$14.05
3	В	14	106	\$246.25	\$15.39
4	В	9	102	\$227.25	\$14.20
1	NB	9	108	\$196.50	\$12.28
2	NB	13	101	\$188.50	\$11.78
3	NB	14	106	\$194.00	\$11.88
4	NB	9	102	\$196.25	\$12.27

Table 1.1: Session Summary

1. Treatment B = Barter, Treatment NB = No Barter

2. Does not include payouts to overbooked subjects.

1.5 Experimental Design

In the experiment, subjects were initially endowed with one of three items: a red ticket (the primary currency), a blue ticket (the secondary currency), or a non-perishable good. All subjects were matched in every period, equivalent to $\alpha = 1$. Subjects earned 1 point by trading with another subject for a good they could consume, and subjects could not consume a good with which they were endowed or already held. With probability *x* subjects could consume the good of their trading partner, assuming the partner held a

good. Thus, the single coincidence of wants was x, and in the treatment in which trade (barter) was allowed between two good holders, the double coincidence of wants was x^2 . In the treatment in which trade between two good holders was not allowed, effectively $x^2 = 0$. Each point earned translated into \$0.25 that went towards the subjects' cash payouts at the end of the experiment.

A single coincidence of wants of x = 0.80 was used in all sessions and treatments. All subjects were informed, both in the instructions and all computer screens, that there was an 80% probability that when they were matched with a good holder, they could consume that good holder's good. Subjects were also informed that the computer would randomly draw a number over a uniform distribution [0, 1] and that if the number was less than or equal to 0.80, the computer would determine that there was a single coincidence of want. If the number drawn was greater than 0.80, the computer would determine there was not a single coincidence of want. For clarity, subjects were asked to think of a 10-sided die. If a 1, 2, 3, 4, 5, 6, 7, or 8 was rolled, the subject could consume his or her trading partner's good. If a 9 or 10 was rolled, the subject could not consume his or her trading partner's good, and therefore no trade was possible.

In order to induce a discount factor, subjects were informed that the experiment was broken down into a number of sequences, or supergames, that in turn were broken down into an indefinite number of trading periods. Each sequence consisted of at least one trading period, and continued with a new period with probablity $\beta = 0.90$ and ended with a probablity of $(1 - \beta)$. Time permitting, when a sequence ended, a new sequence would begin. Importantly, for the first period of each sequence, subjects were randomly endowed with a new item, as determined by the computer, regardless of the item that they held in the last period of the previous sequence. At the end of each period, on the results screen (see Figure 1.2), subjects were told whether or not a new period would begin, and if not, what item they would carry into the first period of the next sequence.

Figure 1.2: Results Screen



For all sessions and treatments, the discount factor β was set to 0.90. Therefore, subjects were informed that there was a 90% probability that the current sequence would continue with a new period, and a 10% probability that the sequence would end. Similar to determining single coincidence of want, subjects were asked to think of rolling a 10sided die, and when a 1, 2, 3, 4, 5, 6, 7, 8, or 9 was rolled, the sequence would continue with a new period, and if a 10 was rolled, the sequence would end. In addition, subjects' trading screens displayed a chart of the cumulative probability of the sequence ending within 1 to 10 periods from the current period (see Figure 1.3). The trading screen also displayed the cumulative blue ticket acceptance rate for the sequence.

Figure	1.3: N	/lain	Screen
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In the underlying model, the rate of time preference *r* rather than the discount factor β appears. For determining the mixed strategy equilibrium, *r* is therefore calculated as:

$$r = \frac{1-\beta}{\beta} \approx 0.11 \tag{1.10}$$

The number of periods in each sequence were randomly determine by the computer in advance of the beginning of a session, and was unknown to the subjects ⁷. The number of sequences in a session was capped to limit the total number of trading periods to approximately 100 for time considerations. Again, this was unknown to the subjects. In order to ensure comparability of treatments, the number of sequences and periods for the first sessions of the barter treatment and no barter treatment were held the same, likewise for the second sessions of the barter treatment and no barter treatment, etc. See Table 1.2 for the number of sequences and periods for each session.

In a trading period, subjects were randomly and anonymously matched with another subject - their trading partner for that period. If the rules of the experiment allowed (described below), the matched pair was offered the opportunity to trade the items they held. If trade occurred, the subject that traded for a good would "consume" that good, earn one point and then produce a new good that was carried into the next period, assuming the sequence continued. The subject that received a ticket in trade would carry that ticket into the next period, again assuming the sequence continued. If both subjects in a pair held a good and were able to trade and chose to do so, they would both consume the good for which they traded, earn one point, and produce a new good to be carried into the next round of the sequence. If subjects could not trade, they would carry their current good into the next period if the sequence continued.

As noted previously, at the beginning of each sequence, subjects were endowed

⁷An R script using the "runif" command was used for the random number generation.
	S13 S14	1	101	90 106	, ,	int sequences
	S12		85	89	ı	squivale
	S11	ı	59	88	ı	have e
	S10	ı	48	<i>6L</i>	ı	tments
ince #	S9	108	43	69	102	er trea
Seque	S8	74	37	65	6L	bart
	S7	73	31	43	57	nd nc
	S6	70	28	42	56	rter a
	S5	65	24	38	43	he ba
	S4	51	13	21	18	for t
	S3	37	12	18	17	sions
	S2	24	11	12	∞	ig ses
	S1	10	4	11	S	ondin
		Session 1	Session 2	Session 3	Sessoin 4	1. Corresp

Table 1.2: Ending Period Number of Each Sequence

with one of three items: a red ticket (the primary currency), a blue ticket (the secondary currency), or a good. For all sessions and treatments, there were 4 red ticket holders, 4 blue ticket holders, and 8 good holders.⁸ Subjects were then matched in pairs of two, and if the rules of the game allowed, were offered the opportunity to trade. To summarize:

- If a ticket holder is matched with a good holder, and the ticket holder can consume the good holder's good (there is a single coincidence of want), the ticket holder may offer to trade items.
- If a good holder is matched with a red ticket holder, the computer will automatically accept an offer to trade on behalf of the good holder.
- If a good holder is matched with a blue ticket holder, the good holder may decide whether or not to trade with the blue ticket holder.
- Barter Treatment: If two good holders are matched, and both matched trading partners can consume the others good (i.e. there is a double coincidence of wants), each may offer to trade. Trade only occurs when both matched subjects agree to trade.
- No Barter Treatment: If two good holders are matched, they may not trade.

⁸I was limited by the number of available work stations available in the lab.

Subjects made trading decisions before knowing the decision of the subject with whom they were matched.

Given the above parameter settings, the barter and no barter models give predictions as to the mixed strategy equilibrium. Specifically:

Barter

$$\Pi_{s} = \left(\frac{xr + x^{2}\alpha\mu_{g} + x\alpha\mu_{p}}{r + x\alpha(\mu_{g} + \mu_{p})}\right) = \frac{0.8 * 0.11 + 0.8^{2} * 1 * 0.5 + 0.8 * 1 * 0.25}{0.11 + 0.8 * 1(0.5 + 0.25)} = 0.86$$
(1.11)

<u>No Barter</u>

$$\Pi_s = \frac{x \alpha \mu_p}{r + x \alpha (\mu_s + \mu_p)} = \frac{0.8 * 1 * 0.25}{0.11 + 0.8 * 1(0.5 + .025)} = 0.28$$
(1.12)

These predictions for the mixed strategy equilibria, being evolutionarily unstable, also act as thresholds for determining in which direction blue ticket acceptance rates should move. For example, in the barter economy, if the fraction of subjects accepting blue tickets is at any point below 0.86, the model predicts that the acceptance rate will eventually degenerate to zero. Likewise, if the fraction of subjects accepting blue tickets is at any point above 0.86, the model predicts that the acceptance rate will explode to 1, i.e. 100% acceptance. As the no barter partial acceptance equilibrium (0.28) is lower, the likelihood of full acceptance in the no barter economy is higher, and for full rejection, lower.

1.6 Experimental Results

This sections presents the findings from the two treatments described above. Findings include both within and between treatment analysis at an individual, session, and treatment level. Specifically, I analyze the difference in acceptance rates between the two treatments, changes in acceptance rates over the course of a session, and subjects' individual patterns of acceptance and rejection of the secondary currency.

Finding 1. Secondary currency acceptance rates were higher in the no barter treatment versus the barter treatment.

The underlying theory predicts that it is more likely that a secondary currency will be accepted when barter is not possible. Though secondary currency acceptance rates were positive in both treatments, acceptance rates were considerably higher in the no barter treatment. Table 1.3 displays, for each session, the cumulative acceptance rates of blue ticket offers broken down into three time periods: 1) acceptance rates for the first 25 offers, 2) acceptance rates for subsequent offers, and 3) total acceptance rates across the entire session. A Wilcoxon Mann-Whitney non-parametric test of all four sessions of each treatment for each of the three time periods indicates that the no barter treatment had significantly higher blue ticket acceptance rates in all cases (p-value = 0.021 in all three cases). See Table 1.4 for a summary of the Wilcoxon results, including comparisons of sessions split by first half versus second half.

Treatment,	# of	Average over Periods			
Session	Periods	First 25	Remaining	Total	
B, S1	108	0.48	0.23	0.26	
B, S2	101	0.52	0.36	0.38	
B, S3	106	0.44	0.59	0.57	
B, S4	102	0.56	0.26	0.30	
B Avg		0.50	0.36	0.39	
NB, S1	108	0.80	0.90	0.88	
NB, S2	101	0.72	0.72	0.72	
NB, S3	106	0.72	0.80	0.79	
NB, S4	102	0.72	0.74	0.74	
NB Avg		0.75	0.80	0.80	

 Table 1.3: Blue Ticket Acceptance Rates

B = Barter, NB = No Barter

Table 1.4: Barter vs. No Barter Mann-Whitney Mean Comparisons

Periods	Acceptance Rate Comparison	P-Value
1st 25	No Barter > Barter	p=0.021
Post 25	No Barter > Barter	p=0.021
1st Half	No Barter > Barter	p=0.021
2nd Half	No Barter > Barter	p=0.043
All	No Barter > Barter	p=0.021

A graphical depiction of this results is displayed in Figure 1.4. In the graph, the horizontal axis is the cumulative number of blue ticket for good offers made, while the vertical axis is the cumulative number of such offers accepted. The black line represents a hypothetical session in which all blue ticket offers are accepted. Blue ticket acceptance in the no barter treatment sessions (red), are all higher than the barter treatment sessions (blue) and this divergence occurs early, evident before the 25th blue ticket offer in each session. This suggests that, in aggregate, subjects were willing to

risk trading a good for a secondary currency without enforceable acceptance as trading options were limited given the inability to barter.



Figure 1.4: Cumulative Blue Ticket Acceptance Rate

Finding 2: Subjects were initially willing to "test the waters" and accept blue tickets in exchange for goods, though this willingness dissipated relatively quickly in the barter treatment.

Again referring to Figure 1.4, with the exception of session 3, barter treatment sessions show a distinct leveling off of blue ticket offer acceptances over time, suggesting a certain amount of learning by subjects. A Wilcoxon Mann-Whitney non-parametric tests does not find a statistically significant difference between the average acceptance rates in the first 25 offers versus the subsequent offers for the barter treatment sessions (p = 0.127). However, excluding session 3 the same test does suggest a significant difference (p = 0.050). Further evidence of this phenomena is apparent in the bar graph in Figure 1.5 which visually shows the difference in acceptance rates before and after the 25th blue ticket offer. The underlying evolutionary theory suggests a reason for this behavior, as the higher unstable mixed strategy equilibrium in the barter model requires fewer subjects unwilling to accept a secondary currency to cause a degeneration to the 100% rejection equilibrium.



Figure 1.5: Acceptance Rates by Period: Barter

Notedly, a similar pattern is not evident in the no barter sessions. While Figure 1.6

suggests subjects in aggregate slightly increased their willingness to accept blue ticket offers, a Wilcoxon Mann-Whitney non-parametric tests does not find a statistically significant difference between the average acceptance rates in the first 25 offers versus the subsequent offers (p=0.189). This fits with both the theory and the behavior observed in the barter treatments: a portion of subjects are initially willing to accept the secondary currency, but as the mixed strategy equilibria is lower in the barter treatment, a relatively smaller group of subjects accepting the currency is needed to push the equilibrium towards full acceptance.



Figure 1.6: Acceptance Rates by Period: No Barter

Finding 3: Subjects who have previously had a blue ticket offer rejected are less likely to subsequently accept blue ticket offers, particularly when barter is not possible. In order to determine whether previous experience with having a blue ticket offer

rejected impacted subjects' future decisions as good holders, I ran multiple randomeffects probit regressions, the results of which are displayed in Table 1.5.⁹ In the regressions, the dependent variable is whether or not a subject accepted a blue ticket offer in exchange for his or her good (0 = reject, 1 = accept). *Barter* is a dummy variable for the treatment (0 = no barter, 1 = barter), and *NewSequence* is a dummy for whether or not the offer occurred at the beginning of a new sequence (0 = no, 1 = yes). *RejectCumul* is the cumulative number of blue ticket offer rejections the subject received during the current sequence prior to making a decision whether or not to accept such an offer, and *RejectCumul* * *Barter* is an interaction term. *RejectSeq* is a dummy variable indicating whether or not the subject had a blue ticket offer rejected during the current sequence prior to making a decision whether or not to accept sequence is a dummy variable indicating whether or not the subject had a blue ticket offer rejected during the current sequence prior to making a decision whether or not to accept a blue ticket offer regardless of the number of times such a rejection occurred (0 = no, 1 = yes). *RejectSeq* * *Barter* is also an interaction term.

The results in Table 1.5 suggest that previous experience did impact subjects' decisions as to whether or not to accept blue tickets in exchange for their good. Both the binary rejection and cumulative rejections variables were significant and negative, suggesting that having a blue ticket offer rejected in turn reduced the likelihood that a subject would accept a blue ticket offer in the same sequence. Moreover, the impact of a rejection was larger in the barter treatment, as indicated by the statistically signif-

⁹Following Duffy and Puzzello (2014), I use the gllamm package for Stata 12 to estimate the regressions, with robust standard errors clustered at the individual and session level.

	Accept = 1, Reject = 0					
	(1)	(2)	(3)	(4)		
Barter	0.023	0.040*	0.015	0.038		
	(0.024)	(0.024)	(0.026)	(0.029)		
NewSequence	-0.048	-0.048	-0.049	-0.050		
1	(0.056)	(0.056)	(0.055)	(0.055)		
Period	0.000	0.000	0.000	0.000		
	(0.001)	(0.001)	(0.001)	(0.001)		
Re jectCumul	-0.210***	-0.122***				
	(0.036)	(0.016)				
RejectCumul * Barter		-0.154***				
U U		(0.059)				
Re jectSeq			-0.394***	-0.229***		
5 1			(0.067)	(0.067)		
RejectSea * Barter				-0.290***		
				(0.101)		
Constant	-0.060	-1.208***	0.000	-0.060		
	(0.010)	(0.034)	(0.030)	(0.034)		
Observations	13,344	13,344	13,344	13,344		
Log Likelihood	-3429.095	-3427.386	-3425.195	-3421.605		
Standard errors in parentheses						
*** p< 0.01 , ** p< 0.05 , * p< 0.1						

Table 1.5: Probit Regression of Blue Ticket Acceptance

icant and negative results for both rejection - barter interaction terms. There was no indication of a reset effect at the beginning of a sequence, nor of changes in decision making behavior due to the length of the session as both the new sequence and period coefficients were insignificant.

Finding 4: All three strategies - always accept a blue ticket, always reject, or mix - were evident in all treatments. However, the always accept strategy was most common

in the no barter treatment, and the mixed strategy predominated.

While the underlying money search model does not explicitly assume or predict agent learning, the evolutionary dynamics suggest that as a subject learns whether or not other subjects will accept a secondary currency, the subject will adjust his or her behavior accordingly. In Figures 1.7 to Figure 1.10, I compare, by treatment and session, individual subject decisions as to whether or not to accept a blue ticket in exchange for a good. The horizontal axis is the period number, the vertical axis is the individual subjects (in no specific order), and the vertical black lines demarcate the end of a sequence. A blue circle indicates the subject accepted a blue ticket offer, and an orange triangle indicates the subject rejected a blue ticket offer. The top chart in each figure shows the results from the barter treatment, and the bottom chart shows the results from the no barter treatment.

One noticeable pattern consistent with the aggregate findings mentioned above is that in the barter treatments, individual subjects often (though clearly not always) appear to initially be willing to accept blue tickets, but after a few trades, revert to rejecting all such future offers. Clear examples of this behavior are subjects 7 and 11 in session 1 (Figure 1.7a); subjects 7, 8, 10, 12, and 13 in session 2 (Figure 1.8a); and subjects 3, 6, 8, 10, and 15 in session 4 (Figure 1.10a). Again, session 3 of the barter treatment is an outlier with no subjects clearly displaying this learning behavior (Figure 1.9a).

However, there are also several subjects in the barter treatments who rejected all, or

almost all, blue ticket offers from the beginning of the session, examples being subjects 4, 15, and 16 in Figure 1.7a; subjects 9 and 16 in Figure 1.8a; subject 8 in Figure 1.9a; and subjects 2 and 8 in Figure 1.10a. Presumably, these subjects have "chosen wisely" and therefore experience no incentive to change their behavior. In contrast, there are relatively few subjects who played a pure strategy of complete acceptance, subject 13 in Figure 1.7a, subject 15 in Figure 1.9a, and subject 15 in Figure 1.10a being the only examples. In this last case, the subject only had three blue ticket offers so may not have had enough experience to persuade a change in behavior.

The remaining subjects in the barter treatment sessions display varying degrees of mixed strategy behavior. Some subjects, such as subject 2 in Figure 1.7a appear to have played a pure strategy of always reject with a temporary "testing of the waters" but in the middle of the session rather than the beginning. In general, a subject deciding to play a mixed strategy may be the result of a multitude of factors, such as experiencing only sporadic rejection of their own blue ticket offers and therefore not clearly identifying the general aggregate trend, attempting to signal to other players to accept blue tickets, or possibly not fully understanding the strategic choices faced.

The most noticeable trends among subjects within the no barter treatment sessions are the number of subjects who played a strategy of always accepting a blue ticket offer. Subjects 1, 12, 13, and 14 in session 1 (Figure 1.7b); subjects 1, 9, 12, 13, and 14 in session 2 (Figure 1.8b); subjects 1, 2, 9, 13, and 15 in session 3 (Figure 1.9b); and

subjects 5, 7, and 8 in session 4 (Figure 1.10b) chose this strategy. Moreover there we 18 subjects across the four no barter sessions that predominantly played an always accept strategy who, early in the session, rejected a blue ticket offer one or two times. While the remaining subjects played mixed strategies, most of these subjects more often than not chose to accept blue ticket offers.

A possible explanation for this behavior in the no barter treatment is that subjects realized the strategy that maximizes welfare is for everyone to always accept blue ticket offers. Thus, in both treatments subjects initially attempted to play this strategy. However, in the no barter treatment, since good-for-good trades may not occur, subjects needed to have a ticket of either color for trade to be possible. Therefore, the incentive to defect when others defect was significantly mitigated, consistent with the evolution-ary dynamics of the theoretical model.



Figure 1.7: Blue Ticket Acceptance Decisions: Sessions 1 (a) Barter Treatment







Figure 1.8: Blue Ticket Acceptance Decisions: Sessions 2 (a) Barter Treatment







Figure 1.9: Blue Ticket Acceptance Decisions: Sessions 3 (a) Barter Treatment







Figure 1.10: Blue Ticket Acceptance Decisions: Sessions 4 (a) Barter Treatment





1.7 Conclusion

For a currency to become a generally accepted medium of exchange, people must believe that if they accept the currency in trade, they will in turn be able to trade the currency for goods or services in the future. For a commodity or commodity-backed money, the value of the money outside of exchange encourages this belief. However, with token money, generating general acceptance is more complicated, as beliefs about acceptance may unravel: if people believe no one will accept the money in the future, they are not willing to accept the money in the present, a process that becomes a selffulfilling prophesy. When an existing, generally accepted medium of exchange already exists, the need to accept a new money is greatly reduced, thus further complicating the acceptance dynamic.

In this paper, I analyze this dynamic by testing a dual currency, money search model in a controlled laboratory setting. I find that even when a fully accepted currency already exists an economy, a secondary currency may still be readily accepted. Moreover, this acceptance is significantly higher when barter does not exist, highlighting the benefit of money in overcoming a lack of a double coincidence of wants. In contrast, in an economy in which barter does exist, acceptance of a secondary currency does exhibit the potential to unravel.

Chapter 2

Secondary Currency Acceptance in an Agent-Based Model with Adaptive Learning

2.1 Introduction

In this chapter, I employ agent-based models ("ABMs") to explore the dynamics of the dual-currency, money search model from Kiyotaki and Wright (1993) as described in the previous chapter. Like laboratory experiments, ABMs allow researchers to test theory in a controlled setting and to analyze emergent behaviors of agents that lead (or not) to equilibria. However, unlike experiments, ABMs also provide researchers with the opportunity to test many more parameter settings with a large number of heterogeneous agents over a longer period of time than would be possible with human subjects.

The use of the term agent-based model (sometimes called agent-based computational economics or ACE) is relatively recent, arguably dating to the late 1990s to early 2000s. However, the methodology itself has a longer history, and was often referred to as "artificially intelligent agents" (Marimon et al 1990) or "artificial adaptive agents" (Holland and Miller 1991). Generally, these terms refer to the use of computer simulations in which a number of agents are programmed to follow individual behavioral rules and/or learning processes, and these rules and processes may be different between each agent, groups of agents, or common to all agents. Agents then interact with each other, and these interactions often lead to the emergence of complex aggregate behaviors.

In the field of macroeconomics, the "bottoms up" approach of ABMs is distinct from more traditional economic simulations in which models without analytical solutions, often dynamic stochastic equilibrium models (DSGE), are solved numerically in order to find equilibrium values and test various economic shocks. DSGE models generally entail homogeneous, representative agents and impose a high-level economic structure, i.e. a "top down" approach. ABMs, in contrast, provide the opportunity to model agents with significant heterogeneity of beliefs, endowments, utility functions, etc. While a macroeconomic model may be used as the basis for an ABM, ABMs arguably allow for more realistic simulation of real economies given agent heterogeneity. Moreover, agent-level analysis allows researchers to track and analyze emergent behaviors and patterns and how these behaviors and patterns affect whether or not the system as a whole converges to a steady state. The results may then be compared with the predictions of the underlying macroeconomic model. Arifovic (2000) provides a comprehensive overview of such use of ABMs for macroeconomic modeling, focusing particularly on agent learning via genetic algorithms.

Agents in ABMs may follow predefined, static rules or may employ one of the multitude of learning algorithms, i.e. artificial intelligence, typically when the agents are attempting to maximize or minimize a specific value such as utility or production costs. These learning rules may be adaptive, looking only at past actions, or predictive, attempting to forecast future events and optimize based upon these predictions. Moreover, learning may be individual in that agents only consider the results of their own actions, or social, allowing agents to incorporate the results of the actions taken by other agents (Arifovic et al 2013, Arifovic et al 2016). Examples of individual, adaptive learning include Roth-Erev (Erev and Roth 1998) and probabilistic learning, while genetic algorithms, which I employ in this research, may be either individual or social.

2.2 Literature Review

An early example of using a form of genetic algorithms in money search models is Marimon et al (1990). The authors of this paper test the predictions of a Kiyotaki and Wright (1989) search model in which there are three commodities, each with different holding costs, and agents that may not consume their own production good. The underlying learning mechanism used is a classifier system in which agents choose from a set of predefined rules, or classifiers, that consist of strings that encode what action to take given the current state of the world. Each gene in the string may take one of three values: 0, which indicates the state doesn't exist (or to reject an offer); 1, which indicates the current state does exist (or to accept an offer), and #, which indicates there is no preference of which action to take given the current of genetic-like variation. The results of this research indicate that while the classifier system may converge to an equilibrium in which the lowest cost good is used as a medium of exchange - the fundamental strategy - the ability to converge to a speculative equilibrium is limited.

Based on the same theoretical model as Marimon et al (1990), Staudinger (1999) employs a genetic algorithm in which binary strings directly encode agents' strategies, thereby removing the need to rely on classifiers. Reproduction, crossover, and mutation operations are then applied to the strings, with utility used as a measure of fitness. Supporting Marimon et al (1990), Staudinger (1999) finds that agents tend to converge to a fundamental strategy. However, when a high discount rate is employed, agents increase the number of times they converge to the speculative strategy.

Arifovic (1996) uses genetic algorithms in a simulation of the dual currency, over-

lapping generations model of Kareken and Wallace (1981). The genetic algorithm encodes in binary strings both an agent's decision as to the amount to save (versus consume) and what proportion of the savings to allocate to each currency. The standard genetic operations of reproduction, crossover, and mutation are employed, as well as an election operation that pre-tests new strings based on the utility they would have generated in the previous round of trade. Arifovic (1996) finds that, under genetic algorithm dynamics, the monetary equilibrium of the Kareken and Wallace (1981) model is unstable, and that even if agents temporarily converge to an equilibrium in which all agents use the same strategy, the invasion of different strategies due to the genetic operators pushes the system out of equilibrium. Arifovic (2001) tests a similar model but introduces a government agent that finances deficits via seigniorage. In this research, the author finds that agents converge to the use of the currency of the government with the smaller deficit.

2.3 Theory

2.3.1 Model

The theoretical models used in my ABMs are the same as in the previous chapter describing the dual currency experiment. Below is a review of the equations. The Bellman's equations for the dual currency model with barter are:

$$rV_g = \alpha \mu_g x^2 (U - V_g) + \alpha \mu_p x \max_{\pi_p} \pi_p (V_p - V_g) + \alpha \mu_s x \max_{\pi_s} \pi_s (V_s - V_g)$$
(2.1)

$$rV_p = y_p + \alpha \mu_g x \Pi_p (U + V_g - V_p)$$
(2.2)

$$rV_s = y_s + \alpha \mu_g x \Pi_s (U + V_g - V_s) \tag{2.3}$$

where agents may be good (g) holders, primary (p) currency holders, or secondary (s) currency holders with population proportions μ_g , μ_p , and μ_s , respectively, and $\mu_g + \mu_p + \mu_s = 1$. U is utility, x is the fraction of goods an agent can consume (single coincidence of want), α is the matching technology, $y_{p,s}$ is currency-specific dividend returns, and r is the rate of time preferences. Π_p and Π_s are the probabilities a good holder will accept a given type of currency (taken as given by a currency holder), and π_p and π_s are a good holder's best responses.

The unstable, mixed equilibrium when the primary currency is always accepted but the secondary currency may or may not be accepted by good holders is:

$$\Pi_{s} = \left(\frac{xr + x^{2}\alpha\mu_{g} + x\alpha\mu_{p}}{r + x\alpha(\mu_{g} + \mu_{p})}\right)$$
(2.4)

As noted previously, the only difference between this dual currency model with barter and the model without barter is the good holder's Bellman's equation (Colacelli and Blackburn 2009). In the case of the model with no barter, this equation is:

$$rV_g = \alpha \mu_p x \max_{\pi_p} \pi_p (V_p - V_g) + \alpha \mu_s x \max_{\pi_s} \pi_s (V_s - V_g)$$
(2.5)

The mixed strategy equilibrium for the no barter model is then:

$$\Pi_s = \frac{x \alpha \mu_p}{r + x \alpha (\mu_g + \mu_p)} \tag{2.6}$$

The parameter settings are the same as those used in the laboratory experiments, specifically x = 0.8, $\alpha = 1$, $\mu_p = 0.25$, $\mu_s = 0.25$, $\mu_g = 0.5$, and $r \approx 0.11$ (that is, the discount factor $\beta = 0.9$). Thus, the mixed equilibrium for the no barter treatment is 0.28 and 0.86 for the barter treatment.

2.3.2 Learning

The agents in my ABMs use genetic algorithms in order to determine the optimal secondary curreny acceptance rate, using cumulative utility as a fitness measure. Genetic algorithms employ multiple steps that replicate biological genetic reproduction, as described below. Moreover, some measure of fitness is needed in order to determine which strings (chromosomes) provide greater benefit to the agents. In many economic applications, the measure of fitness is cumulative utility. Learning by genetic algorithms may also be individual or social. Individual learning occurs when each agent has its own string(s) that undergo genetic operations independent of other agents, while social learning uses the pool of strings of the population of existing agents. This latter approach, used in my research, is often employed when there is a want to model some level of communication between agents.

The steps typically employed by genetic algorithms include (Holland 1992, Arifovic 1996):

Selection / Reproduction. Selection and reproduction (sometimes just referred to as reproduction) replicates strings in order to create a new generation of offspring. The likelihood that any given string will produce one or more offspring is contingent on the string's relative fitness, thus increasing the fitness of the population over time. Two types of reproduction are most common:

Roulette wheel: An agent is drawn from the current population, with the probability of a given agent being drawn from the population weighted by its relative fitness. Often, this is done *N* times, *N* being the size of the current population. This ensures a constant population size.

Tournament: Several strings from the current population are randomly selected, and the string from this selection with the highest fitness is added to the population of offspring. This is also typically done with replacement.

• Crossover. In the crossover operation, two offspring are chosen randomly, and a random gene position in their chromosomes is selected, the same for each string. The offspring then swap genes on either side of this selected location. For exam-

ple, if the chromosomes consist of 10 genes, two offspring might look like: [1 0 1 1 0 1 0 0 1 1] and [0 0 0 1 1 1 0 1 0 0]. If position 4 is randomly selected, and crossover occurs, the resulting agents chromosomes would be [1 0 1 1 1 1 0 1 0 0] and [0 0 0 1 0 1 0 0 1 1]

- Mutation: Mutation, often called experimentation, ensures some genetic diversity always exists in the population of strings and thus there is always some probability that an unrealized string may enter the population. With mutation, there is some probability p_{mut} that a gene in an agent's string changes. In the case of binary genes, a 1 is flipped to a 0 or a 0 flipped to a 1.
- Election. In some implementations of genetic algorithms, an election operation is used. Typically, this involves comparing the fitness of the two offspring postmutation with the fitness of their original two parents. Two of the four strings are chosen based on which strings have the higher fitness, and these two strings are added to the new population. However, in order to use election, it must be possible to assign some level of fitness to the post-mutation offspring, which is not always possible. The benefit of election is that it aids in controlling for too much diversity in the population that might prevent convergence to a steady state.

Not all genetic algorithms employ all four mechanisms, and which mechanisms are employed is often dependent on the model structure. Moreover, a mechanism may be altered to better fit the requirements of the model. For example, if the chromosome is a decimal number rather than its coinciding binary encoding, it may not be possible to perform standard crossover procedures as swapping digits between two decimal numbers may cause large jumps in a chromosome's value. Thus some modified procedure must be used.

2.4 Methodology

I code agent-based models using the Netlogo platform (Wilensky 1999). Netlogo is a programming language and development platform that provides multiple tools to efficiently create ABMs and includes such functionality as visual guides for the creation of real-time graphs, settings controllers, and other graphical elements. The Netlogo programming language is a dynamic language that is interpreted at runtime, and thus does not require manual compiling of the code. Moreover, the language is also dynamically typed, removing the need to declare variables in advance. All of these elements add to the speed and efficiency with which Netlogo models may be created. Figure 2.1 is a screenshot of the ABM dashboard for the binary-based genetic algorithm ABM. Included are controls for setting parameters on the left, real-time graphs of the mean and standard deviation of agents' secondary currency acceptance rates in the middle, and a graphical representation of the agents and their trading linkages on the right.

The ABMs I develop consist of 100 agents, 50 of which are initially endowed with a good, 25 with a red ticket that acts as the primary currency, and 25 with a blue ticket





The dashboard for the decimal ABM differs slightly in that the initial acceptance rates and the number of periods per run

are set manually due to differences in the underlying Netlogo code.

that acts as the secondary currency. Agents are randomly matched each period with another agent and may trade if one or both of the agents holds a good and there is a coincidence of want (single coincidence for a currency-for-good trade and double for a good-for-good barter trade). Agents earn 1 utility point when they trade for and consume a good, though agents may not consume their own good. After consuming a good, agents produce a new good which they carry into the next trading period. If agents do not trade in a period, they carry their current item into the next period. In order to induce a discount factor, at the beginning of every period there is a probability that all agents will randomly be assigned a new item regardless of the item agents held in the previous period. This implementation mimics that of the laboratory experimental design.

The trading rules under which the agents operate are:

- If an agent holding a good is offered a red ticket, the agent must accept the ticket.
- If an agent holding a good is offered a blue ticket, the agent may decide whether or not to accept the offer.
- If an agent holding a ticket of either color is matched with an agent holding a good and there is a single coincidence of want, the agent holding the ticket always offers to trade.

The last rule differs from the rule used in the human subject experiment. In the experiment, subjects holding tickets could decide whether or not to trade. As subjects

almost always did so given that this is a dominant strategy, I program the agents in the ABMs to always play this strategy. The benefit of doing so is that agents only need to learn whether or not to accept a ticket in trade for a good, simplifying the learning process and the underlying genetic algorithm.

Agents adjust the probability that they will accept a blue ticket (the secondary currency) in exchange for a good via a genetic algorithm. I employ two different genetic algorithms, one which uses binary numbers in the underlying algorithm which are then decoded into a decimal number and normalized to the interval [0, 1] and one in which a decimal number acceptance rate is used directly.

As described previously, the standard genetic algorithm approach entails encoding an agent's strategy in a binary string (the chromosome). In my first ABM, a chromosome consists of 15 genes, i.e. has length l = 15, each of which may be a 1 or $0.^1$ Thus, the chromosome may represent a decimal number from 0 to 32,767. As secondary currency acceptance rates are in the interval [0,1], an agent's binary string chromosome must first be converted to a decimal number and then divided by 32,767. However, as pointed out by Arifovic (1996), the problem with such an approach is that during mutation, changing a few number of bits from 0 to 1 or vice versa in a binary number may cause a significant change in the corresponding decimal number. One solution is to use gray code binary numbers. In gray code, adjacent decimal integers have corresponding

¹15 bits were chosen based upon Arifovic (1996) and the fact that the decoded real numbers, once normalized to a decimal number in the interval [0, 1] allow for a relatively high degree of precision which may be important for convergence

binary number that differ by only one bit. For example, the binary numbers corresponding to the decimal numbers 19 and 20 are 10011 and 10100, respectively. The two binary numbers have three bits that differ. The corresponding gray code binary numbers for 19 and 20 are 11110 and 11111, which differ by only one bit. Thus, using gray code helps to ensure that if a few number of bits are changed, the decoded decimal number also changes by a relatively small amount. This reduces the probability of the high variability that may occur during genetic algorithm operations, variability which might unduly prevent the population from converging.²

Unlike some models in which the genetic algorithm is run every period, the algorithm I implement is run every τ periods, with $\tau \in \{5, 10, 30\}$ depending on the parameter settings. This alternative method is used because agents all face the same gain in utility for consuming a good and only one good per period may be consumed by any given agent. Therefore, fitness differentiation between strategies over one period is limited. τ may be thought of as a string's or chromosome's lifespan.

As agents may carry the same item from one period to the next, genetic operations may not involve the birth and death of agents as this would result in the redistribution of items. Rather, agents' strategies, as encoded in their binary string chromosomes, undergo genetic operations which are run for each agent separately. In the first step, reproduction, two agents are selected by tournament: 5 agents are randomly drawn from the population and the agent with the highest utility is selected and its chromosome,

²Gary Polhill graciously shared relevant Netlogo code.

in gray code, is copied. This process is then repeated. In the next step, two new chromosomes are created from the copied chromosomes via crossover at a randomly determined bit position. The original agent's chromosome is then replaced by one of the two new chromosomes via random selection. Finally, the new chromosome undergoes mutation, with probability $p_{mut} \in \{0.01, 0.033, 0.1\}$ that any given bit will flip from 0 to 1 or vice versa, consistent with many other studies including Arifovic (1996) and Arifovic and Maschek (2012). This chromosome is then decoded and normalized to a decimal number in the interval [0, 1] and becomes the agent's secondary currency acceptance probability for the next trading period. Thus, the new generation consists of the original agents with new chromosomes.

The decimal implementation of a genetic algorithm differs from the binary form in several ways as there is no encoding / decoding between decimal and binary numbers. First, reproduction uses a roulette wheel, rather than tournament, selection process in which the probability of an agent (the parent) being drawn from the population for reproduction is weighted by that agent's relative fitness. Following Arifovic (2001), the parent's cumulative utility is then compared to that of the agent for which the genetic algorithm is being run, and if the parent's cumulative utility is higher, the agent copies the parent's acceptance rate. Finally, mutation, if it occurs, consists of adding a random number in the interval [-1, 1] to the agent's acceptance rate, the result having a floor of 0 and a ceiling of 1.

An issue with the variation caused by mutation arises with both implementations as such variation can be detrimental to convergence in the later stages of a simulation (Arifovic and Karaivanov 2010, Arifovic et al 2013). Therefore, in addition to using a constant mutation rate, I also run simulations in which the rate of mutation decays over time at a rate of 0.95:

$$p_{mut,t} = p_{mut}(1 - 0.95(t/T)) \tag{2.7}$$

where $p_{mut,t}$ is the probability of mutation at period *t*, and *T* is the total number of periods in a simulation, in this case 5000.

While agents' acceptance rates are randomly initialized on the uniform distribution [0, 1], I also test the models for robustness by running simulations in which the initial acceptance rates are the opposite of the expected equilibrium. Specifically, I test initializing all agents to 100% acceptance in the barter treatment and 0% acceptance in the no barter treatment.

Typical computing time for one simulation - one set of parameters with 100 runs - was approximately 10 minutes running on a computer with an Intel i5-3210 2.50ghz processor and 8gb of RAM. Given the number of parameter settings, there were a total of 144 simulations for an approximate total run time of 24 hours.

2.5 Results and Discussion

They key finding of the simulations is that under many parameter settings with a random initialization of agents' acceptance rates on the interval [0,1], but particularly the baseline settings of $p_{mut} = 0.033$, $\tau = 30$ rounds and a declining mutation rate, the models tend to converge to the predicted equilibria. When agents are able to barter, the mean agent acceptance rate of the secondary currency across all runs over the last 100 rounds³ averages 2.9%, displayed in Figure 2.2. Conversely, in Figure 2.3, if agents cannot barter, the mean acceptance rate averages 95.2%.⁴.

Figure 2.2: Barter, $p_{mut} = 0.033$, $\tau = 30$, and Declining Mutation Rate



³Using the last 100 rounds is based on the methodology from Arifovic et al (2012) ⁴All data is available in the tables in Supplementary Materials



Figure 2.3: No Barter, $p_{mut} = 0.033$, $\tau = 30$, and Declining Mutation Rate

When the genetic algorithms are set to use a constant mutation rate, the baseline settings display strikingly similar results to the experimental outcomes, likely due to the link between mutation in the ABMs and experimentation by subjects in the laboratory experiments. In the no barter treatment, with $p_{mut} = 0.033$ and $\tau = 30$, the ABM converges to a 84.4% acceptance rate over the last 100 periods (Figure 2.4) while the average acceptance rate in the experimental setting was 80% over all periods. The barter treatments differ slightly more: the ABM converges to a 13% acceptance rate (Figure 2.5) and the average acceptance rate for the experimental economy is 39%.

Other parameter settings also display similar convergence as the baseline settings, but often with much more variation. For example, with $p_{mut} = 0.01$, many runs con-


Figure 2.4: No Barter, $p_{mut} = 0.033$, $\tau = 30$, Constant Mutation Rate

Figure 2.5: Barter, $p_{mut} = 0.033$, $\tau = 30$, Constant Mutation Rate





Figure 2.6: Barter, $p_{mut} = 0.01$, $\tau = 30$, Declining Mutation Rate

verge later in the simulations and there is greater variation between runs with the same parameter settings, as seen in Figure 2.6 and Figure 2.7, though as expected, this was less pronounced with declining mutation rates. Likewise, with a high mutation rate $(p_{mut} = 0.10)$, the simulations show significant variation between runs, and the average across all 100 runs typically settles some distance from the theoretical equilibria.

The underlying search model under deterministic evolutionary dynamics predicts that agents should converge to 100% acceptance of the secondary currency when the population acceptance rate is greater than the mixed equilibrium, and to the 0% rate when below. However, Kandori et al (1993) show that in evolutionary coordination games with mutation, agents will converge to the stable equilibrium with the larger



Figure 2.7: No Barter, $p_{mut} = 0.01$, $\tau = 30$, Declining Mutation Rate

basin of attraction regardless of initial conditions. To test this, I initialize all agents' acceptance rates to 0% in the no barter model in which the mixed equilibrium is approximately 28%. The results of the simulations follow the predictions of Kandori et al (1993) in that agents converge towards a 100% acceptance rate in contrast to the 0% equilibrium predict by the search model (Figure 2.8). Likewise, following a similar procedure with the barter treatment (which has a mixed equilibrium at the 86% acceptance rate level) and initializing at 100%, the agents converge towards the 0% acceptance rate (Figure 2.9).

The alternative genetic algorithm that uses a decimal number in place of a binary string often performs considerably better than the binary number algorithm under the



Figure 2.8: No Barter, Initial 0%, $p_{mut} = 0.033$, $\tau = 30$, Declining Mutation Rate





same parameter settings (see Table B.5 to Table B.8 in Supplementary Materials). In fact, the decimal based algorithm often converges completely to 100% acceptance in the no barter treatment and 0% acceptance in the barter treatment under a declining mutation rate. Notably, however, this algorithm struggles with low p_{mut} combined with high τ when agents' acceptance rates are initialized to 100% in the barter treatment and 0% in the no barter treatment. For example, in the no barter treatment with a declining mutation rate $p_{mut} = 0.033$, $\tau = 30$ and all agents initialized to 0% acceptance, the economy is unable to break away from the 0% stable equilibrium. In general, the results from the decimal version of the genetic algorithm should be viewed with caution, however, as the methodology is relatively uncommon in existing research and therefore not well tested.

2.6 Conclusion

The general results of the ABMs I simulate in this paper closely match with the experimental results explored in the previous chapter, and depending on the parameter settings, often converge close to one of the stable equilibria predicted by the underlying dual currency, money search model. This later finding is particularly true with declining mutation rates. Moreover, agents' learning via genetic algorithms is often in line with Kandori et al (1993) that predicts that agents in evolutionary coordination games with mutation will converge to the stable equilibrium with the larger basin of attraction irregardless of initial conditions. However, certain parameter settings that introduce too little or too much diversity into the population, or don't provide enough time for the algorithms to learn, make it difficult for the underlying genetic algorithms to reach a steady state or the stable equilibrium with the larger basin of attraction.

Part II

International Capital Flows and U.S.

Monetary Policy

Chapter 3

International Capital Flows vs. the Federal Reserve as Determinants of U.S. Interest Rates

In a 2005 speech to the Virginia Association of Economists, then-Federal Reserve Board governor Ben Bernanke stated that a significant influx of savings from foreign countries, rather than profligate spending by U.S. consumers, drove the large U.S. current account deficit during the first half of the 2000s. He famously called this large inflow of foreign funds into U.S. asset markets a global saving glut (Bernanke 2005). Others have pointed to the glut as the cause of the divergence in movement between short-term and long-term rates that began in the early 1990s, a phenomena that former Fed Chairman Greenspan (2005) described as a "conundrum" and analyzed by Rudebusch et al (2006) and Bandholz (2009). (See Figure 3.1)



Figure 3.1: 10-Year Treasury and Effective Funds Rates

While global savings as a percent of GDP did increase significantly in the 2000s, it is only slightly higher than the increase observed in the 1970s. However, what is unique about the later period is the massive growth in savings by emerging markets, particular Asian, much of which flowed into the United States and other developed, western nations (Wolf 2008. See Figure 3.2).

Three reasons for this glut are often cited. First, Asian governments (most prominently) may be accumulating large foreign currency reserves, most often in U.S. dol-



Figure 3.2: Gross National Savings as a % of GDP

lars, in order to drive export-led economic growth via low exchange rates. Second, in response to the Asian financial crisis of the late 1990s, governments may be stockpiling reserves as an insurance policy against another similar crisis. Finally, rising oil prices provided a windfall profit to oil exporting countries which they invested in U.S. Treasury and federal agency securities. The textbook" result, according to Bernanke, was a decrease in real interest rates.

However, recent debate about the global saving glut has not centered around U.S. trade deficits, but rather the causes of the 2007-2008 financial crisis. Many economists argue that the Federal Reserve, by keeping short-term rates too low during the 2000s,

created an unsustainable housing bubble that inevitably collapsed. For example, Taylor (2009) specifically points to the deviation between the overnight federal funds rate and the interest rate prescribed by a standard Taylor rule as evidence of loose monetary policy. Federal Reserve Chairman Bernanke, however, continues to support the savings glut causation argument, and instead places the blame for the crisis on misguided housing policy and lax bank supervision (Bernanke et al, 2011).

The Federal Reserve's response to the financial crisis has created a new dimension to the dynamics of the Treasury market, in some ways similar to the foreign Treasury purchase phenomena. Specifically, the Fed's large scale asset purchases ("LSAP") program has focused on reducing long-term rates and expectations of future rates, though unlike FOI Treasury purchases the Fed's actions are in direct response to economic stress.

Significant research has been undertaken on Federal Reserve quantitative easing policy, both pre- and post-crisis, and to a lesser extent on foreign participation in the U.S. Treasury market. However, no studies of which I am aware attempt to estimate the impacts of both factors, though FOI's share of the Treasury securities market is significantly larger than that of the Fed's (see Figure 3.3). My research seeks to determine the impact, if any, of both quantitative easing ("QE") during the recent recession simultaneously with the impact foreign Treasury securities purchases may have had. In addition, unlike past research, I include not only foreign government flows into Treasury notes

and bonds, but also bills and Treasury Inflation-Protected Securities (TIPS).



Figure 3.3: Foreign Official and Federal Reserve Treasury Market Share

This paper is structured as follows. Section 2 reviews the literature on both foreign purchases of U.S. Treasury securities and recent studies of the Fed's QE programs. Section 3 provides a detailed description of, and the methodologies for cleansing, the relevant data. Section 4 describes the empirical models employed for analysis. Section 5 reviews the results.

3.1 Literature Review

There are two strands of literature relevant to my research: 1) analysis of foreign purchases of U.S. Treasury securities, and 2) analysis of Federal Reserve purchases. This later area of research has grown considerably in the last few years in response to the Fed's quantitative easing programs

3.1.1 Foreign Purchases

Warnock and Warnock (2009) is perhaps the seminal paper analyzing the impact of foreign Treasury purchases on U.S. interest rates. The authors perform an empirical analysis of such capital inflows into the U.S. during the time period 1984 to 2005. Specifically, they consider the impact of foreign government purchases of long-term U.S. Treasury and federal agency securities on U.S. long-term rates, focusing on the nominal 10-year Treasury yield. For purposes of their analysis, foreign government purchases are the result of government policy and not profit seeking. Warnock and Warnock (2009) also briefly considers the impact of these capital inflows on other interest rates, such as Corporate Aaa bonds and mortgage rates, though this is not the main focus of their paper.

In Warnock and Warnock (2009), the 10-year nominal yield is modeled as a function

of inflation expectations, 3 month LIBOR, an interest rate risk premium, expected GDP, U.S. government deficits, and foreign purchases of U.S. Treasury securities. In order to control for issues of non-stationarity and cointegration, they restrict the coefficients on LIBOR and 10-year inflation expectations to sum to one, under the assumption that real interest rates are stationary. The authors estimates that \$100B annual foreign government purchases of U.S. Treasury securities put between 50 80 bps downward pressure on long-term Treasury rates. They find their results to be consistent with other studies, including Laubach (2009) and Bernanke et al (2004), though these latter studies did not focus on foreign capital inflows.

Bertaut et al (2011), estimating a model similar to Warnock and Warnock (2009) and the model used in this paper, find that a \$100 billion increase in FOI purchases of U.S. Treasury notes and bonds decreases 10-year yields by 11 to 15 basis points. A more recent study, Beltran et al (2013), also uses a similar model but with a few key differences, including different measures for the risk premium and normalizing Treasury securities holdings by the total debt outstanding held by the public minus Federal Reserve holdings. Again, their findings are similar to Warnock and Warnock (2009). Notably, none of these studies include Federal Reserve Treasury flows, and instead Fed policy is solely reflected in the inclusion of the Fed Funds rate or some short-term rate proxy.

3.1.2 Federal Reserve Securities Purchases and QE

A prominent study by Hamilton and Wu (2012) of monetary policy at the zero lower bound (ZLB") uses pre-crisis data and an affine term structure model to estimate the impact of Federal Reserve Treasury securities purchases during the time period 1990 to 2007. Their findings suggest that a \$400 billion dollar purchase of long-term securities by the Fed would lower the 10-year rate by 14 basis points. This is in line with the event study by Gagnon et al (2011) which finds that such a purchase would have a -20 basis point impact.

In another event study by Krishnamurthy and Vissing-Jorgenson (2011), the authors focus on the multiple channels through which the Fed's quantitative easing programs of 2008-2009 (QE1) and 2010-2011 (QE2) impacted yields. They find evidence for inflation, liquidity and signaling channels, and note that purchases of different securities (mortgage-backed securities versus Treasury securities) had disproportionate impacts by security type. Moreover, the authors estimate that the impact of QE1 reduced 5 to 10-year Treasury yields by 20 to 40 basis points.

D'Amico and King (2010) employ a two stage, cross-sectional regression model to analyze the Federal Reserve's purchases of Treasury securities during 2009. To test the portfolio balance and preferred habitat theories, their analysis groups the Fed's purchases by different maturities. They estimate that on the day of a purchase announcement, yields declined by 3.5 basis points, and that the cumulative impact of all purchases (\$300 billion) was 50 basis points. A linear projection suggests that a \$400 billion purchase would have an impact of -67 basis points, notably higher than the estimate of Hamilton and Wu (2012). The largest impact was on 10- to 15-year yields, suggesting imperfect substitution between different maturities given that the Fed focused on purchases of longer term securities.

3.2 Data

Perhaps the most important data for an analysis of the impact of foreign purchases of U.S. Treasury securities, yet the most difficult to attain, are figures on foreign sales and purchases of such securities. One possible source is the Federal Reserve which maintains weekly data on its custodial holdings of foreign official institutional holdings of U.S. government securities. The immediate issue with this data is that it does not include foreign private holdings. Moreover, private parties may hold U.S. government securities on behalf of foreign governments, and these holdings are not included in the Federal Reserves data. To further complicate the Federal Reserves data, foreign official institutions also includes non-government international institutions. Lastly, the Fed reports foreign holdings data every Wednesday, rather than end of the month figures which are needed to match the frequency of data of other variables used in this analysis.

I therefore use data from the U.S. Treasury International Capital (TIC) system in order to sidestep some of these issues. The Treasury conducts monthly surveys of holders of U.S. Treasury securities in order to determine foreign official and private holdings of U.S. Treasury bills and other short-term securities at a country level, and this data is readily available on their website¹. Until 2012, however, the Treasury only conducted annual surveys every June of foreign holdings of U.S. Treasury notes and bonds, but did collect estimates of monthly flows (Brandner et al 2012). Therefore, the Treasury would use the annual survey holdings figures as a baseline, and back out monthly holdings by consecutively adding net monthly flows. Then, when the data from the following June annual survey was available, the Treasury could verify its monthly estimates. The results often showed some discrepancy between the estimated procedure and the annual survey results, especially with holdings of federal agency securities. (See Figure 3.4)

Therefore, I rely on data provided by Bertaut and Tryon (2007) and Warnock and Warnock (2009) who attempt to solve this problem by smoothing out the discrepancies. First, naive estimates of monthly foreign holdings of Treasury securities are created following the method used by the Treasury. Then, estimates of changes in the prices of Treasury securities and transaction costs are calculated. Taking these factors into account, Bertaut and Tryon calculate the residual between their monthly estimate and the annual survey data. This residual is then allocated across monthly holdings based on that month's portion of total net annual transactions.

This smoothed data was only available up to June 2011. However, as mentioned

¹http://www.treasury.gov/resource-center/data-chart-center/tic/Pages/ticliab.aspx



Figure 3.4: Foreign Official Holdings: Annual Survey vs Monthly Flows Estimates*

previously, in February 2012 the Treasury started collecting monthly data on foreign holdings of Treasury notes and bonds, in addition to bills. In order to fill this 6 month gap and maintain consistency, I use updated data through December 2013 from Bertaut and Judson (2014). I rely on data from the U.S. Treasury's Major Foreign Holders of Treasury Securities" for the time period January 2014 to April 2014. ²

There is one remaining issue with the Treasury TIC data. Foreign holdings of Treasury notes and bonds are reported at market value, while holdings of Treasury bills (and all other relevant data on U.S. government debt) are reported at face value. In

²An email correspondence with Ruth Judson confirmed that the Treasury's recent estimates are consistent with the smoothed estimates

order to adjust the Treasury notes and bonds data, I initially used the Lehman Treasury Securities Index which tracks the change in market value of a portfolio of Treasury notes and bonds. Unfortunately, this index is only available until 2008 due to Lehman's bankruptcy at that time. Further investigation revealed, however, that Barclay's had purchased the division of Lehman that managed this index and continues to track it.³. I therefore use this updated index to convert foreign holdings of Treasury notes and bonds from market to face value.

Federal Reserve outright holdings of Treasury securities data through 2010, including TIPS, comes from Hamilton and Wu (2012) who collected historical data from the Federal Reserve's H.4.1 statements. I verified and update this data with figures available from the Federal Reserve's FRED website.⁴ The available data breaks down the Fed's holdings by remaining (not face) maturity, i.e. securities maturing within 1 year, between 1 to 5 years, between 5 to ten years, and greater than 10 years. This maturity breakdown is helpful in that it allows a more accurate analysis of the Fed's recent large scale asset purchases which essentially traded all of the Fed's holdings of short-term securities for medium to long-term securities (such maturity level breakouts, unfortunately, are not available for foreign holdings). (See Figure 3.5)

Data on the U.S. Treasury's marketable securities outstanding also comes from Hamilton and Wu (2012) who break down securities data by current weekly maturity.

³I attained this data with the gracious help of Christopher Darringer at Barclays. ⁴http://research.stlouisfed.org/fred2/



Figure 3.5: Maturity Structure of Federal Reserve Treasury Holdings

As before, however, their data ends in 2010. Moreover, it does not include Treasury Inflation-Protected Securities (TIPS"), though the Federal Reserve and foreign holdings data does. In order to update their data and add in TIPS values, I collected security-level data from individual releases of the U.S. Treasury's Monthly Statement of the Public Debt." Specifically, I created a database that includes records of individual Treasury securities outstanding, by CUSIP and month, starting in 1997 for TIPS data and 2011 for all securities. I duplicated the structure of the data set from Hamilton and Wu (2012), and then merged the two datasets, backfilling TIPS data. (See Figure 3.6)

Interest rate data for the effective federal funds rate and constant maturity 2-year,



Figure 3.6: Maturity Structure of U.S. Marketable Treasury Debt Outstanding

5-year and 10-year yields data comes from the Federal Reserve's FRED website. As a proxy for economic volatility, I use the CBOE's S&P 500 Volaility Index (See Figure 3.7). This data comes from the CBOE and Bloomberg.⁵ Data on expectations of future inflation at 2 year, 5 years, and 10 years out comes from the Cleveland Federal Reserve, and is based on professional forecasts and asset market data as proposed by Haubrich (2009). The Cleveland Fed did not release this data set until recently, and therefore was not available to earlier topical research such as Warnock and Warnock (2009) (See Figure 3.8).

⁵http://www.cboe.com/micro/VIX/vixintro.aspx



Expectations of 1-Year ahead GDP come from the Blue Chip survey and, for values not available in 2005, the Cleveland Federal Reserve "Economic Trends" publication.⁶ The available "Economic Trends" data matches well with the Blue Chip survey, and the period in question was one of relatively stable growth expectations.

3.3 Model

My model is similar to the OLS flow model of Warnock and Warnock (2009) and to a lesser extent, Bertaut et al (2011), with a few key differences. To capture the Fed's

⁶http://www.clevelandfed.org/research/trends/2005/0805/trends.pdf



conventional monetary policy, I use the effective fed funds rate, rather than three month LIBOR, as the Fed arguably has greater control of the former. In order to control for economic volatility, I use a measure of equity market volatility as does Beltran et al (2013) whereas Warnock and Warnock (2009) and Bertaut et al (2011) use the 36 month rolling standard deviation of interest rates. The reason cited to include this variable is that an increase in rate volatility may cause investors to demand a higher yield in order to compensate for the risk that rates may be lower when the investors debt instruments mature. However, Sarkar and Ariff (2002) argue that the relationship between volatility and interest rates should be negative, as the government may to a certain extent time its

borrowings, and thus essentially holds an option that it exercises when interest rates are lower. Moreover, when interest rates are volatile, investors have some incentive to lock in rates through the purchase of debt instruments.

Unlike much of the previous research, I also do not subtract Fed holdings from the marketable Treasury securities outstanding values as Fed flows into Treasury securities are a variable in my model. Moreover, in order to account for the fact that the Fed's recent QE operations have essentially removed from its balance sheet any Treasury securities with a maturity of less than one year, I split the Federal Reserve's flows into two separate variables based on maturity. Not doing so may confound the impact of the maturity structure change in the Fed's balance sheet. Another noticeable difference between my model and previous research such as Warnock and Warnock (2009), Bertaut el al (2011) and Beltran et al (2013) is that I have included foreign purchases of U.S. Treasury bills. Such purchases, while smaller than that of Treasury bond and notes, are not insignificant (see Figure 3.9). Moreover, as all outstanding bills must have a remaining maturity of less than 1 year, bills holdings become important when analysing maturity structures.

I have also not included U.S. federal government surplus or deficit data. Arguably, the budget balance acts as a supply-side flow. However, as several variables in the model are normalized by marketable Treasury securities outstanding, an increase or decrease in the government's debt is to a certain extent already reflected. In addition,



Figure 3.9: Foreign Official Holdings of Treasury Bills vs Notes and Bonds

tests of alternate model specifications including a surplus/deficit variable showed no significant differences in results.

Thus, the model I employ is

$$i_{t,m} = \beta_0 + \beta_1 EFFR_t + (1 - \beta_1)\pi_{t,m} + \beta_2(\pi_{t,1} - \pi_{t,m}) + \beta_3 FOI + \beta_4 FED_{t,<1}$$
(3.1)
+ $\beta_5 FED_{t,>1} + \beta_6 VIX + \beta_7 GDP_{t,exp}$

where *i* is a nominal interest rate, *m* is the maturity, *EFFR* is the effective federal funds rate, and π is expected inflation. *FOI* is the 12-month flow of foreign government purchases of Treasury securities normalized by lagged marketable Treasury securities

outstanding. $Fed_{<1}$ and $Fed_{>1}$ are the 12-month flows of Federal Reserve purchases of Treasury securities with a remaining maturity of less than 1 year and greater than 1 year, respectively. Both variables are normalized by lagged marketable Treasury securities outstanding of matching maturities. *VIX* is the S&P 500 Volatility Index and GDP_{exp} is the expected 1 year ahead growth in U.S. real GDP.⁷

3.3.1 Econometric Issues

Several issues should be noted about this model. First is the possibility of endogeneity - that is, the right hand side variables are responding to changes in the nominal interest rate. This is less of an issue for macro-economic variables, as such variables react slowly to changes in interest rates, an assumption often used in macro modeling (Warnock and Warnock 2009). The assumption of exogeneity is weaker for the effective federal funds rate and forward looking variables. Finally, I have focused on foreign government rather than foreign private flows into Treasury securities. Previous models, with the exception of Beltran (2013), have assumed that the former are exogenous, as FOI purchases are often in response to government policy rather than driven by profit seeking motives (Dooley et al 2004) and are significantly greater in magnitude (see Figure 3.10). However, as Beltran et al (2013) note, there is some evidence that this is not necessarily the case and therefore may be a strong assumption.

⁷The difference between 1-year inflation expectations and longer term inflation expectations is included to capture the additional impact of the former.



Figure 3.10: Foreign Holdings of U.S. Treasury Securities

There is also a potential issue of stationarity of the dependent variable and cointegration. As Warnock and Warnock(2009) notes, both interest rates and inflation expectations have drifted lower over the past 20 or more years (See Figure 3.1 and Figure 3.8). There is a possibility, therefore, that an unrestricted regression would pick up this longer term relationship between the variables and not shorter term relationships. Following Mehra (1998) and Warnock and Warnock (2009), I have addressed this issue by imposing the restriction that the coefficients on expected inflation and the effective federal funds rate sum to one under the belief that Treasury security yields are non-stationary and cointegrated with these two variables.

3.3.2 Data issues

. One potential issue with the data used is that the Federal Reserve's Treasury holdings data doesn't include the impact of repurchase (repo") or reverse repo agreements. Repos, at least temporarily, increase the Federal Reserve's Treasury holdings, and reverse repos decrease holdings. While it is true that repos and reverse repos tend to be short-term in nature, often a matter of days, a continual rolling over of such agreements would be essentially the same as an outright sale or purchase of Treasury securities by the Fed. Netting out the Fed's repos and reverse repos provides some clarity. As can be seen in Figure 3.11, until early 2008, the Fed's ongoing net Treasury holdings from temporary open market operations were relatively small and constrained. However, in 2008, the Fed's use of repos significantly increased, effectively increasing the Fed's Treasury holdings. Maturity breakdowns of repos, however, are not readily available. Therefore, as a check I estimate additional regressions with data that ends in 2007.



Figure 3.11: Value of Net Repurchase Agreements

3.4 Results

I estimate the model for the 2-year, 5-year, and 10-year Treasury yields (see Table 3.1 to Table 3.3)⁸. I also estimate the model over the full dataset from 1990 to 2014 and over a sub-sample of the data from 1990 to 2007 in order to control for the potential change in market dynamics due to the recent financial crisis.

⁸The reason for including the 5-year rate is that it is closest to the average maturity of foreign Treasury holdings (Beltran et al 2013) This is verified by the data provided in the U.S. Treasury's annual Foreign Portfolio Holdings of U.S. Securities''

	1990-2014	1990-2007		
EFFR	0.720***	0.542***		
	(0.023)	(0.042)		
π_2	0.280***	0.458***		
	(0.023)	(0.042)		
$\pi_1 - \pi_2$	-1.594***	-1.325***		
	(0.248)	(0.337)		
FOI	-0.012	-0.046**		
	(0.012)	(0.018)		
$FED_{<1}$	0.016	-0.111**		
	(0.011)	(0.048)		
$FED_{>1}$	-0.045***	-0.003		
	(0.010)	(0.087)		
GDP	0.001***	-0.002*		
	(0.000)	(0.000)		
VIX	-0.0003***	-0.0004***		
	(0.000)	(0.000)		
Constant	0.009***	0.025***		
	(0.0013)	(0.003)		
Ljung Box Test	467.644***	2315.463***		
R^2	0.947	0.908		
Observations	280	192		
Robust standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				
-	-			

Table 3.1: 2-Year Treasury Rate

One problem of note is the presence of autocorrelation, a problem also present in Warnock and Warnock (2009), Bertaut el al (2011) and Beltran et al (2013). Ljung Box Q tests reject the null of no autocorrelation in my estimates. To account for this, I have used Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors.

For the sub-sample 1990-2007, all models show that FOI purchases of Treasury

	1990-2014	1990-2007
EFFR	0.496***	0.236***
	(0.028)	(0.043)
π_5	0.504***	0.764***
	(0.028)	(0.043)
$\pi_1 - \pi_5$	-1.102***	-0.931***
	(0.192)	(0.236)
FOI	-0.011	-0.094***
	(0.017)	(0.017)
$FED_{<1}$	0.041***	-0.076*
	(0.015)	(0.046)
$FED_{>1}$	-0.066***	-0.218**
	(0.014)	(0.092)
GDP	0.001**	-0.003***
	(0.000)	(0.000)
VIX	-0.0003***	-0.0004***
	(0.000)	(0.000)
Constant	0.017***	0.041***
	(0.002)	(0.003)
Ljung Box Test	883.674***	1097.257***
R^2	0.907	0.877
Observations	280	192
Robust stand	lard errors in p	arentheses

 Table 3.2: 5-Year Treasury Rate

 1000 2014
 1000 2007

*** p<0.01, ** p<0.05, * p<0.1

	1990-2014	1990-2007
FFFR	0 310***	0.051
LTT	(0.020)	(0.031)
—	(0.029)	(0.046)
n_{10}	(0.090)	(0.949)
	(0.029)	(0.048)
$\pi_1 - \pi_{10}$	-0.599***	-0.375
	(0.169)	(0.258)
FOI	-0.005	-0.101***
	(0.015)	(0.018)
$FED_{<1}$	0.053***	-0.009
	(0.014)	(0.049)
$FED_{>1}$	-0.071***	-0.279***
	(0.015)	(0.099)
GDP	0.0005	-0.004***
	(0.001)	(0.001)
VIX	-0.0002***	-0.0004***
	(0.000)	(0.000)
Constant	0.024***	0.051***
	(0.002)	(0.003)
Ljung Box Test	1612.264***	1307.143***
R^2	0.857	0.828
Observations	280	192
Robust stand	dard errors in pa	arentheses
*** p<0.0)1. ** $p < 0.05$.	* p<0.1

 Table 3.3: 10-Year Treasury Rate

 1990.2014
 1990.2007

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securities had a significant impact on interest rates with the expected negative sign (i.e. purchases put downward pressure on yields), and a larger impact on the long end of the yield curve. Federal Reserve purchases of long-term Treasury securities are also estimated to have a significant impact on 5-year and 10-year yields, and as with FOI purchases, the impact is greater on longer-term yields. Purchases of short maturity securities by the Fed, as expected, show a significant effect on short and medium term yields. All of these results suggest some segmentation in the Treasury market. The VIX volatility measure is significant and negative in all models, supporting the thesis that increased market volatility results in a flight to safety" effect. Interestingly, an increase in expected GDP growth is estimated to have a negative impact on interest rates. The reason for this is not clear, but may be an indication of endogeneity.

Results are different when including the 2007-2014 time period in the regressions. FOI flows show no significant impact on Treasury yields. A possible explanation for this is that as short-term yields hit the zero lower bound, longer-term yields also hit a floor, but FOI purchases continued to increase significantly (see Figure 3.10). This may also explain the estimated impact of Fed purchases of longer-term maturities that, while significant, are muted. The findings of Swanson and Williams (2014) suggest that before 2011, the ZLB was not binding on longer term interest rates, but became so after 2011. Fed purchases of short-term securities are either insignificant or positive, likely the result of the fact that during its recent QE programs, the Fed dropped almost all of its holdings of short-term Treasury securities from its balance sheet. The volatility measure continues to show a significant, negative impact on yields. However, GDP expectations over the full sample exhibit either a positive effect (2 and 5 year yields) or no effect (10 year yields), more in line with economic theory.

The results of this paper are mostly consistent with previous research on foreign flows into Treasury securities when estimating over the 1990 - 2007 time period. My estimates of FOI flows have a slightly larger impact on 10-year Treasury yields than comparative studies, with a \$100 billion increase in Treasury holdings lowering the 10year rate by 35 basis points (see Table 3.4). Conversely, I estimate a slightly smaller effect of FOI flows on the 5-year rate compared to Beltran et al (2013), 33 basis points versus 39 - 62 basis points, respectively (see Table 3.5). As mentioned previously, when estimating the model using the full sample, I find that the impact of FOI purchases is insignificant.

Study	Basis Points
Bertaut et al (2011)	-11
Warnock (2009)	-15 to -32
Rudebusch et al (2006)	None
This paper: 1990 - 2007	-35
This paper: 1990 - 2014	None

Table 3.4: FOI Impact of \$100 billion of U.S. Treasury Securities on the 10yr Yield

In comparison to other research on the impact of Federal Reserve purchases of Treasury securities on yields, I find a larger impact over both the sub sample 1990-2007

Study	Basis Points
Beltran et al (2013)	-39 to -62
This paper: 1990 - 2007	-33
This paper: 1990 - 2014	None

Table 3.5: FOI Impact of \$100 billion of U.S. Treasury Securities on the 5yr Yield

and the full sample when considering Treasury securities with a remaining maturity of greater than one year. However, I estimate a smaller impact for purchases of securities with a remaining maturity of less than 1 year (see Table 3.4). This is not necessarily inconsistent with previous studies, as these studies did not split Federal Reserve purchases by maturity, and tended to focus on QE operations which typically occur when short-term yields are pushing against a zero lower bound.

Table 3.6: Fed: Impact of \$100 billion of U.S. Treasury securities on the 10yr yield

Study	Basis Points
D'Amico and King (2011)	-17
Gagnon et al (2011)	-5
Hamilton and Wu (2012)	-4
Krishnamurthy and Vissing-Jorgensen (2011)	-17
This paper: Maturity < 1yr, 1990 - 2007	None
This paper: Maturity < 1yr, 1990 - 2014	18
This paper: Maturity > 1 yr, 1990 - 2007	-99
This paper: Maturity > 1yr, 1990 - 2014	-25

3.5 Conclusion

In this paper, I have attempted to estimate the impact of foreign official and Federal Reserve purchases of U.S. Treasury securities during the time period 1990 - 2014 and a sub sample period from 1990 - 2007. Unlike previous models, I include both types of purchases in the same model. Moreover, I include purchases of Treasury bills, a not insignificant component of foreign official Treasury security portfolios. I find strong evidence, mostly in line with previous research, that both types of purchases have a significant impact on interest rates across the yield curve, though with a larger impact on medium and long-term yields.
Appendix A

Supplementary Materials for "Secondary Currency Acceptance: Experimental Evidence with a Dual Currency Search Model"

Included below are:

- Instructions for the no barter and barter treatment experiments.
- Quiz given prior to beginning an experiment.

A.1 Instructions for the No Barter Treatment Experiment

Instructions

Welcome to this experiment in the economics of decision making. During todays session, you will be called upon to make a series of decisions. If you follow the instructions carefully and make good decisions, you may earn a considerable amount of money that will be paid to you in cash at the end of the experiment. Please, no communication of any type for the duration of todays session and no use of electronic devices such as smartphones, tablets, and media players.

Please carefully read the instructions below. When all participants are finished, you will answer several brief questions on your computer workstation to ensure that you understand these instructions. If you have any questions, please ask. After we have finished with the instructions and the questions, you will begin making your decisions using the computer workstation. The first sequence will be a practice sequence.

Overview

16 people are participating in todays session. Each participant will make trading decisions in a number of periods. A sequence consists of an unknown number of periods. During a period, participants are randomly matched in pairs of 2 and may be offered the option to trade one of three items, as described further below At the end of

each period, the computer program will draw a random number, specifically an integer in the set 1, 2, 3, 4, 5, 6, 7, 8, 9, 10. Each of these ten integers has an equal chance of being chosen, like rolling a ten-sided die. The program will display the result on all participants screens. If the random number is 1, 2, 3, 4, 5, 6, 7, 8 or 9, the sequence will continue with another period. If the random number is 10, the sequence will end. Thus the chance that a sequence will continue is 9 in 10 (90%) and the probability that a sequence will end is 1 in 10 (10%). If a sequence ends, then depending on the time available, a new sequence will begin. You will start the experiment with 0 points. Over the course of a sequence, you may gain points based on the trading decisions you make. Your point total will carry over from one sequence to the next. Your final point total from all sequences played will determine your earnings for the experiment. Each point you earn is worth \$0.25.

Timing and Pairing

In each period, the 16 participants will be anonymously and randomly matched in 8 pairs, 2 people per pair, and make decisions with one another. Each person may hold one of three items: a good, a red ticket, or a blue ticket. For the first period of each sequence, you will be randomly given one of these three items regardless of the item you held at the end of the previous sequence. There is a 4 in 16 (25%) chance you will receive a blue ticket, a 4 in 16 (25%) chance you will receive a red ticket, and an 8 in 16 (50%) chance you will receive a good. In each period, if the rules (described below)

permit, participants decide whether or not to trade their item with the participant with whom they are paired. A trade occurs if both people are able and agree to trade. If you trade for a good you can consume, you earn 1 point. If the sequence continues with a new period, you will then produce a good and enter the new period holding that good. If you trade for a ticket, you will carry the ticket into the next period.

When you are paired with a participant who holds a good, there is an 8 in 10 (80%) chance that you can consume the good and a 2 in 10 (20%) chance that you cannot. Similar to determining whether a sequence ends, the computer will randomly select an integer from 1 to 10 with each integer having the same chance of being drawn. If the random number is any of the integers from 1 to 8, the computer will determine that you can consume the good. If the number is 9 or 10, you cannot consume the good. This probability is the same for all participants and all goods for the entire session. Note that participants may not consume their own good.

Trading Rules

- You cannot trade for a good you cannot consume.
- If a red ticket holder offers to trade for a good holders good, the offer will automatically be accepted on the good holders behalf.
- If a blue ticket holder offers to trade for a good holders good, the good holder has the option to accept or reject the blue ticket holders offer.
- If two good holders are matched, they may not trade.

• If two ticket holders are matched in a period, regardless of ticket color, they may not trade. Note that participants in the pair carry their current item into the next period.

For a summary of the trading rules, see Table 1 at the end of the instructions.

Computer Interface

You will interact anonymously with other participants using the computer workstations. You will see three types of screens (Figures 1-5 below show sample screens).

Trading Screen Figures 1 & 2. The trading screen is the screen where you make your trading decisions. It is divided into three parts.

Across the top you can see the period number, the number of points you have earned during the current sequence, and your point total for the session.

In the middle of the screen, on the left you can see the item that you have, the item your trading partner has, whether or not you can trade, and if you cannot trade, the reason why. On the right, you can make your trade decision, given that trade is possible. You make your selection by clicking the radio button next to Yes or No and clicking the OK button.

At the bottom of the screen, you are provided with information regarding the current sequence. On the bottom left, you can see the total number of blue ticket offers made to good holders during the sequence, as well as the number of such offers accepted by good holders. After at least one blue ticket trade offer has been made during the

sequence, the screen will also display the historic average blue ticket acceptance rate for that sequence (see Figure 2). This number is the number of blue ticket offers accepted by good holders divided by the number of blue ticket offers. Each participant will also see the chance that they can consume the good of a good holder with whom they are paired. Your private trading history for the sequence is displayed at the bottom of the screen starting in the 2nd period of a sequence (see Figure 2).

On the bottom right is a bar chart indicating the cumulative probability that the sequence will end 1 to 10 periods from the current period. This chart reflects the 1 in 10 (10%) chance that the sequence will end from one period to the next. Observe that this probability is increasing, indicating that it is increasing likely the sequence will end 1 to 10 periods from the current period. As noted above, when a sequence ends, you will be randomly reassigned one of the three items to start the next sequence and will not carry forward your item from the previous period.

Waiting screen, Figure 3. At any point in the experiment if you finish your decision sooner than other participants, you will see a waiting screen with the information available on the top and bottom of the trading screen.

Results screen, Figures 4 & 5. After all participants have made their trade decisions in a period, you will see a results screen that displays the result of your trading decision, the item with which you will enter the next period (assuming the sequence continues), the number of points you earned during the period, the result of the randomly drawn

integer chosen by the computer to determine if the sequence continues, and a message indicating whether or not the sequence will continue. Figure 4 depicts the results screen shown when a sequence continues, and Figure 5 depicts the results screen when a sequence has ended.

Summary

- Participants start with 0 points. Participants will play a number of periods in which they are randomly matched in pairs and may offer to trade items assuming one or both of the participants holds a good and the participant can consume the other participants good.
- A sequence consists of an indefinite number of periods. For the first period of a sequence, participants are randomly given a red ticket, blue ticket, or a good. There is a 4 in 16 (25%) chance of being given a red ticket, a 4 in 16 (25%) chance of being given a blue ticket, and an 8 in 16 (50%) chance of being given a good.
- At the end of a period, the computer randomly draws an integer from 1 to 10 with equal chance and determines whether the sequence continues with another period. If a 1, 2, 3, 4, 5, 6, 7, 8, or 9 is drawn the sequence continues. If a 10 is drawn, the sequence ends. Thus, there is a 9 in 10 (90%) chance that a sequence continues and a 1 in 10 (10%) chance that it ends. If a sequence continues, then

a new period begins. If a sequence ends, then depending on the time available, a new sequence may begin.

- Points are earned by trading for a good you can consume. Point totals accumulate over all sequences.
- To determine whether a participant can consume a good, the computer randomly chooses an integer from 1 to 10 with equal chance. If an integer from 1 to 8 is drawn, the participant can consume the other participants good. If a 9 or 10 is drawn, the participant cannot consume the other participants good. Thus, there is an 8 in 10 (80%) chance that a participant can consume the good and a 2 in 10 (20%) chance that the participant cannot consume the good.
- If a red ticket holder offers to trade for a good holders good, the offer will automatically be accepted on the good holders behalf.
- If a blue ticket holder offers to trade for a good holders good, the good holder has the option to accept or reject the blue ticket holders offer.
- Participants in a pair may not trade if both have tickets, regardless of ticket color.
- Participants in a pair may not trade if both have goods
- At the end of the session, each participants cumulative point total will be converted into cash at the rate of 1 point = \$0.25.

Questions?

Now is the time for questions about the instructions. If you have a question, please raise your hand and an experimenter will come to you.

			PLAYER A	
		Good	Blue Ticket	Red Ticket
			Yes, if the ticket holder can consume the good.	Yes, if the ticket holder can consume the good.
	poo	No	 Blue ticket holder may offer to trade 	 Red ticket holder may offer to trade
	5	110.	• Good holder may accept	• The computer
			or reject the trade.	automatically accepts the trade for the good
				holder.
В	et	Yes, if the ticket holder can consume the good.		
PLAYER	Blue Ticke	 Blue ticket holder may offer to trade. Good holder may accept or reject the trade. 	No.	No.
		Yes, if the ticket holder can consume the good.		
	Red Ticket	 Red ticket holder may offer to trade. The computer automatically accepts the trade for the good holder. 	No.	No.

Table 1: Trade Possible?



Figure 1: Example of first period trading screen

Figure 2: Example of trading screen after the first period of a sequence





Figure 3: Example of the waiting screen

Figure 4: Example of the results screen when a sequence continues





Figure 5: Example of the results screen when a sequence ends

A.2 Instructions for the Barter Treatment Experiment

Instructions

Welcome to this experiment in the economics of decision making. During todays session, you will be called upon to make a series of decisions. If you follow the instructions carefully and make good decisions, you may earn a considerable amount of money that will be paid to you in cash at the end of the experiment. Please, no communication of any type for the duration of todays session and no use of electronic devices such as smartphones, tablets, and media players.

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in the set 1, 2, 3, 4, 5, 6, 7, 8, 9, 10. Each of these ten integers has an equal chance of being chosen, like rolling a ten-sided die. The program will display the result on all participants screens. If the random number is 1, 2, 3, 4, 5, 6, 7, 8 or 9, the sequence will continue with another period. If the random number is 10, the sequence will end. Thus the chance that a sequence will continue is 9 in 10 (90%) and the probability that a sequence will end is 1 in 10 (10%). If a sequence ends, then depending on the time available, a new sequence will begin. You will start the experiment with 0 points. Over the course of a sequence, you may gain points based on the trading decisions you make. Your point total will carry over from one sequence to the next. Your final point total from all sequences played will determine your earnings for the experiment. Each point you earn is worth \$0.25.

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whom they are paired. A trade occurs if both people are able and agree to trade. If you trade for a good you can consume, you earn 1 point. If the sequence continues with a new period, you will then produce a good and enter the new period holding that good. If you trade for a ticket, you will carry the ticket into the next period.

When you are paired with a participant who holds a good, there is an 8 in 10 (80%) chance that you can consume the good and a 2 in 10 (20%) chance that you cannot. Similar to determining whether a sequence ends, the computer will randomly select an integer from 1 to 10 with each integer having the same chance of being drawn. If the random number is any of the integers from 1 to 8, the computer will determine that you can consume the good. If the number is 9 or 10, you cannot consume the good. This probability is the same for all participants and all goods for the entire session. Note that participants may not consume their own good.

Trading Rules

- You cannot trade for a good you cannot consume.
- If a red ticket holder offers to trade for a good holders good, the offer will automatically be accepted on the good holders behalf.
- If a blue ticket holder offers to trade for a good holders good, the good holder has the option to accept or reject the blue ticket holders offer.
- If a good holder is paired with another good holder, and both can consume the others good, the two participants may choose to trade. If only one participant

can consume the others good, or neither can consume the others good, no trade is possible.

• If two ticket holders are matched in a period, regardless of ticket color, they may not trade. Note that participants in the pair carry their current item into the next period.

For a summary of the trading rules, see Table 1 at the end of the instructions.

Computer Interface

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At the bottom of the screen, you are provided with information regarding the current sequence. On the bottom left, you can see the total number of blue ticket offers made

to good holders during the sequence, as well as the number of such offers accepted by good holders. After at least one blue ticket trade offer has been made during the sequence, the screen will also display the historic average blue ticket acceptance rate for that sequence (see Figure 2). This number is the number of blue ticket offers accepted by good holders divided by the number of blue ticket offers. Each participant will also see the chance that they can consume the good of a good holder with whom they are paired. Your private trading history for the sequence is displayed at the bottom of the screen starting in the 2nd period of a sequence (see Figure 2).

On the bottom right is a bar chart indicating the cumulative probability that the sequence will end 1 to 10 periods from the current period. This chart reflects the 1 in 10 (10%) chance that the sequence will end from one period to the next. Observe that this probability is increasing, indicating that it is increasing likely the sequence will end 1 to 10 periods from the current period. As noted above, when a sequence ends, you will be randomly reassigned one of the three items to start the next sequence and will not carry forward your item from the previous period.

Waiting screen, Figure 3. At any point in the experiment if you finish your decision sooner than other participants, you will see a waiting screen with the information available on the top and bottom of the trading screen.

Results screen, Figures 4 & 5. After all participants have made their trade decisions in a period, you will see a results screen that displays the result of your trading decision,

the item with which you will enter the next period (assuming the sequence continues), the number of points you earned during the period, the result of the randomly drawn integer chosen by the computer to determine if the sequence continues, and a message indicating whether or not the sequence will continue. Figure 4 depicts the results screen shown when a sequence continues, and Figure 5 depicts the results screen when a sequence has ended.

Summary

- Participants start with 0 points. Participants will play a number of periods in which they are randomly matched in pairs and may offer to trade items assuming one or both of the participants holds a good and the participant can consume the other participants good.
- A sequence consists of an indefinite number of periods. For the first period of a sequence, participants are randomly given a red ticket, blue ticket, or a good.
 There is a 4 in 16 (25%) chance of being given a red ticket, a 4 in 16 (25%) chance of being given a blue ticket, and an 8 in 16 (50%) chance of being given a good.
- At the end of a period, the computer randomly draws an integer from 1 to 10 with equal chance and determines whether the sequence continues with another period. If a 1, 2, 3, 4, 5, 6, 7, 8, or 9 is drawn the sequence continues. If a 10 is drawn, the sequence ends. Thus, there is a 9 in 10 (90%) chance that a sequence

continues and a 1 in 10 (10%) chance that it ends. If a sequence continues, then a new period begins. If a sequence ends, then depending on the time available, a new sequence may begin.

- Points are earned by trading for a good you can consume. Point totals accumulate over all sequences.
- To determine whether a participant can consume a good, the computer randomly chooses an integer from 1 to 10 with equal chance. If an integer from 1 to 8 is drawn, the participant can consume the other participants good. If a 9 or 10 is drawn, the participant cannot consume the other participants good. Thus, there is an 8 in 10 (80%) chance that a participant can consume the good and a 2 in 10 (20%) chance that the participant cannot consume the good.
- If a red ticket holder offers to trade for a good holders good, the offer will automatically be accepted on the good holders behalf.
- If a blue ticket holder offers to trade for a good holders good, the good holder has the option to accept or reject the blue ticket holders offer.
- Participants in a pair may not trade if both have tickets, regardless of ticket color.
- At the end of the session, each participants cumulative point total will be converted into cash at the rate of 1 point = \$0.25.

Questions?

Now is the time for questions about the instructions. If you have a question, please raise your hand and an experimenter will come to you.

			PLAYER A	
		Good	Blue Ticket	Red Ticket
		Yes, if both players can consume the other's good.	Yes, if the ticket holder can consume the good.	Yes, if the ticket holder can consume the good.
	Good	Either good holders may accept or reject the trade	Blue ticket holder may offer to trade.Good holder may accept or reject the trade.	 Red ticket holder may offer to trade. The computer automatically accepts the trade for the good holder.
PLAYER B	Blue Ticket	Yes, if the ticket holder can consume the good.Blue ticket holder may offer to trade.Good holder may accept or reject the trade.	No.	No.
	Red Ticket	 Yes, if the ticket holder can consume the good. Red ticket holder may offer to trade. The computer automatically accepts the trade for the good holder. 	No.	No.

Table 1: Trade Possible?

A.3 Quizzes



Figure 1: Example of first period trading screen

Figure 2: Example of trading screen after the first period of a sequence





Figure 3: Example of the waiting screen

Figure 4: Example of the results screen when a sequence continues





Figure 5: Example of the results screen when a sequence ends

A.4 Quiz

1) At the end of a period, what is the chance that the sequence will continue with a new period?

--- 0 in 10 --- 1 in 10 --- 2 in 10 --- 3 in 10 --- 4 in 10 --- 5 in 10 --- 5 in 10 --- 7 in 10 --- 8 in 10 --- 9 in 10 --- 10 in 10

2) If you meet a good holder, what is the chance that you can consume the good holder's good?

__ 0 in 10 __ 1 in 10 --- 2 in 10 --- 3 in 10 --- 4 in 10 --- 5 in 10 --- 6 in 10 --- 7 in 10 --- 8 in 10 --- 9 in 10 --- 10 in 10

3) Which color of ticket is always accepted by the computer on a good holder's behalf when it is offered in trade for the good holder's good? __ blue __ red

4) Which color of ticket may be accepted or rejected by a good holder when offered in trade for the good holder's good? __ blue __ red

5) When you enter a new sequence after completing a previous sequence, do you keep your item from the previous period? __ yes __ no

Appendix B

Supplementary Materials for "Secondary Currency Acceptance in an Agent-Based Model with Adaptive Learning"

B.0.1 Notes on Tables

The tables below display the averages of the mean, median, and standard deviation of the last 100 periods of simulations for each parameter setting and genetic algorithm.

Definitions

- Constant: Indicates a constant mutation rate during the simulation.
- Declining: Indicates a decaying or declining mutation rate during the simulation.
- Initialization: How the initial acceptance rates of agents were set at the beginning of a simulation.
- Random: Indicates that agents' initial acceptance rates were set individually from a random draw on the interval [0,1].
- Full: Indicates that agents' initial acceptance rates were all set to 100%.
- None: Indicates that agents' initial acceptance rates were set all set to 0%.

lable B.I	: Algori	ithm = Binary, 1	reatment	= Barter, <i>p</i> ,	mut = Constant
Mutation Rate	ų	Initialization	Mean	Median	Standard Deviation
0.010	S	random	0.275	0.337	0.007
0.010	10	random	0.131	0.168	0.004
0.010	30	random	0.059	0.063	0.001
0.033	S	random	0.433	0.448	0.008
0.033	10	random	0.309	0.342	0.007
0.033	30	random	0.130	0.147	0.003
0.100	5	random	0.478	0.481	0.005
0.100	10	random	0.434	0.440	0.007
0.100	30	random	0.319	0.332	0.003
0.010	S	full	0.276	0.331	0.008
0.010	10	full	0.123	0.166	0.004
0.010	30	full	0.050	0.066	0.002
0.033	5	full	0.391	0.420	0.007
0.033	10	full	0.276	0.307	0.006
0.033	30	full	0.142	0.152	0.004
0.100	S	full	0.471	0.476	0.006
0.100	10	full	0.448	0.453	0.008
0.100	30	full	0.319	0.334	0.001

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Mutation Rate	ч	Initialization	Mean	Median	Standard Deviation
0.010	S	random	0.136	0.213	0.003
0.010	10	random	0.051	0.102	0.0005
0.010	30	random	0.021	0.033	0.0003
0.033	S	random	0.246	0.334	0.003
0.033	10	random	0.081	0.107	0.001
0.033	30	random	0.029	0.035	0.001
0.100	S	random	0.286	0.333	0.006
0.100	10	random	0.122	0.163	0.002
0.100	30	random	0.050	0.056	0.002
0.010	S	full	0.159	0.246	0.001
0.010	10	full	0.069	0.121	0.001
0.010	30	full	0.022	0.121	0.001
0.033	S	full	0.210	0.303	0.007
0.033	10	full	0.074	0.110	0.002
0.033	30	full	0.035	0.042	0.001
0.100	S	full	0.293	0.344	0.009
0.100	10	full	0.132	0.193	0.004
0.100	30	full	0.054	0.064	0.004

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Mutation Rate	Ч	Initialization	Mean	Median	Standard Deviation
0.010	S	random	0.824	0.777	0.005
0.010	10	random	0.883	0.867	0.005
0.010	30	random	0.935	0.929	0.002
0.033	5	random	0.669	0.657	0.007
0.033	10	random	0.766	0.753	0.004
0.033	30	random	0.844	0.841	0.004
0.100	S	random	0.562	0.557	0.004
0.100	10	random	0.598	0.585	0.003
0.100	30	random	0.689	0.686	0.002
0.010	5	none	0.822	0.779	0.007
0.010	10	none	0.881	0.870	0.001
0.010	30	none	0.881	0.704	0.004
0.033	5	none	0.662	0.643	0.006
0.033	10	none	0.749	0.730	0.004
0.033	30	none	0.857	0.848	0.002
0.100	S	none	0.553	0.548	0.004
0.100	10	none	0.609	0.602	0.003
0.100	30	none	0.697	0.686	0.005

Table B.3: Algorithm = Binary. Treatment = No Barter. p_{min} = Constant

lable B.4: A	Igorith	m = Binary, Ire	atment =	No Barter,	$p_{mut} = \text{Declining}$
Mutation Rate	ч	Initialization	Mean	Median	Standard Deviation
0.010	S	random	0.912	0.867	0.004
0.010	10	random	0.939	0.921	0.001
0.010	30	random	0.962	0.950	0.0004
0.033	S	random	0.867	0.834	0.006
0.033	10	random	0.934	0.908	0.003
0.033	30	random	0.953	0.941	0.001
0.100	Ś	random	0.816	0.780	0.006
0.100	10	random	0.898	0.879	0.004
0.100	30	random	0.922	0.910	0.002
0.010	Ś	none	0.909	0.874	0.001
0.010	10	none	0.946	0.931	0.002
0.010	30	none	0.067	0.377	0.001
0.033	Ś	none	0.900	0.854	0.002
0.033	10	none	0.940	0.920	0.003
0.033	30	none	0.960	0.951	0.001
0.100	S	none	0.845	0.772	0.009
0.100	10	none	0.885	0.857	0.003
0.100	30	none	0.933	0.922	0.003

Table R 4: Alonrithm = Rinary Treatment = No Barter n_{min} = Declining

C.d Sidei	: Algorii	nm = Decimal,	l reaumen	= barter, <i>j</i>	$p_{mut} = Constant$
Mutation Rate	ц о	Initialization	Mean	Median	Standard Deviation
0.010	S	random	0.009	0.022	0.002
0.010	10	random	0.003	0.008	0.001
0.010	30	random	0	0.003	0.0003
0.033	5	random	0.041	0.057	0.004
0.033	10	random	0.018	0.023	0.001
0.033	30	random	0.012	0.015	0.001
0.100	S	random	0.154	0.185	0.008
0.100	10	random	0.080	0.086	0.002
0.100	30	random	0.042	0.045	0.002
0.010	5	full	0.008	0.018	0.002
0.010	10	full	0.008	0.129	0.001
0.010	30	full	0.934	0.621	0.003
0.033	S	full	0.037	0.054	0.002
0.033	10	full	0.020	0.026	0.001
0.033	30	full	0.013	0.056	0.001
0.100	S	full	0.149	0.172	0.004
0.100	10	full	0.072	0.080	0.005
0.100	30	full	0.043	0.046	0.002

Table B.5: Algorithm = Decimal. Treatment = Barter. p_{min} = Constant

Mutation Rate	ч	Initialization	Mean	Median	Standard Deviatio
0.010	5	random	0.991	0.985	0.001
0.010	10	random	0.993	0.989	0.001
0.010	30	random	0.996	0.993	0.0005
0.033	S	random	0.962	0.954	0.002
0.033	10	random	0.972	0.967	0.002
0.033	30	random	0.979	0.976	0.001
0.100	S	random	0.882	0.870	0.002
0.100	10	random	0.911	0.904	0.003
0.100	30	random	0.943	0.940	0.0004
0.010	S	none	0.990	0.974	0.003
0.010	10	none	0.008	0.129	0.002
0.010	30	none	0.003	0.006	0.0003
0.033	Ś	none	0.960	0.952	0.002
0.033	10	none	0.958	0.790	0.003
0.033	30	none	0.014	0.019	0.001
0.100	S	none	0.883	0.869	0.005
0.100	10	none	0.915	0.909	0.004
0.100	30	none	0.060	0.114	0.001

Table B 7: Algorithm = Decimal. Treatment = No Barter. n..... = Constan
Mutation Rate	ч	Initialization	Mean	Median	Standard Deviation
0.010	S	random	1	0.994	0.0004
0.010	10	random	1	0.989	0.0001
0.010	30	random	1	0.986	0.0002
0.033	S	random	1	0.996	0.0004
0.033	10	random	1	0.987	0.001
0.033	30	random	1	0.988	0.0005
0.100	S	random	0.996	0.989	0.001
0.100	10	random	0.997	0.992	0.0003
0.100	30	random	0.996	0.994	0.0002
0.010	Ś	none	1	0.848	0.001
0.010	10	none	0	0.081	0.0002
0.010	30	none	0	0.001	0.0002
0.033	S	none	-	0.995	0.001
0.033	10	none	0.964	0.511	0.001
0.033	30	none	0	0.002	0.0002
0.100	S	none	0.994	0.988	0.001
0.100	10	none	0.998	0.993	0.001
0.100	30	none	0	0.014	0.0003

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