Currency Crisis: Evolution of Beliefs, Experiments with Human Subjects and Real World Data

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Abstract

Building on the analysis of Arifovic and Masson (2003), we study a model of currency crisis where agents' beliefs is the only source of volatility containing the potential for devaluation. In addition to simulating this model in laboratory experiments with human subjects, we build our own model of agents' expectations extending upon the original Arifovic and Masson framework. In this model, heterogenous investors have sets of potential rules available for use in each period. Each agent selects a single rule from its set probabilistically; the probability of each rule's selection is based on the relative performance of this rule had it been applied historically. As part of our methodology, we conduct a large number of simulations for different parameter values to check for the robustness of these simulation results. In comparing the properties of the time-series generated by computer simulations and human subjects, we find a number of key similarities. These include large measures of kurtosis, positive skewness, and negative correlation between the first difference in spread statistics. Importantly, this large kurtosis measure is also a feature that characterizes empirical data on the returns in emerging markets.

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1 Introduction

The role of investors' expectations has always been emphasized as a very important factor affecting the behavior observed in the financial markets. In particular, conventional accounts of the episodes of currency crisis focus on changes and shifts in investors' beliefs. However, modeling the changes in investors' expectations that might trigger currency crisis, without any apparent change in economic fundamentals, has not been given much attention in the existing literature.

The traditional rational expectations approach leaves little room for modeling endogenous changes in investors' expectations that would trigger recurrent speculative attacks on currency.[1] The exception are the models that due to the features of the underlying fundamentals exhibit multiple (static) equilibria where it is usually possible to add an exogenous sunspot process that governs switches between the neighborhoods of these equilibria. As a result, sunspot models generate dynamics of the recurrent currency crises.[2] However, they require coordination of investors' beliefs on a particular sunspot process falling short of explanation of why and how this coordination might take place.

Over the last few years, advances have been made with the models that depart from the rational expectations hypothesis, and instead assume that investors are boundedly rational agents who have to learn and adapt over time. Kasa (2001) introduces adaptive learning into Obstfeld's (1997) 'escape clause' model and shows that learning dynamics, rather than sunspots, can generate switches between multiple steady states. Cho and Kasa (2003) introduce learning into a model of Aghion, Bacchetta and Banerjee (2001). Even when equilibrium is unique in this model, they show that the 'escape dynamics' of the learning algorithm produce the kind of Markov-Switching exchange rate behavior that is typically attributed to sunspots. Both of these studies assume homogeneity of investors' beliefs.

Arifovic and Masson (2003) take a different approach and study a dynamic model of currency crisis in which heterogenous expectations of boundedly rational agents evolve through a very simple algorithm that involves imitation and experimentation. Their model generates recurrent crises that result from investors' change in expectations; periods of excessive optimism are followed by periods of excessive pessimism. Currency crises characterized by recurrent periods of devaluations are purely expectationally driven. The model also yields some predictions about the behavior of distributions of beliefs over time (that in fact are linked to recurrent devaluations). Direct empirical tests of these predictions cannot be done as we do not have any data concerning the behavior of investors' beliefs in real markets.

Arifovic's and Masson's model is based on the idea of *social learning* where a population of beliefs of a large number of agents evolves together over time. This concept captures well the fact that a large number of investors participate in trading in real markets. Investors in real markets can also observe the behavior of some of the other investors (captured well by imitation).

We extend Arifovic's and Masson's original framework by using a model (see Arifovic and Ledyard, 2003) where each investor has a collection of alternative beliefs and chooses one of them probabilistically. (The evolution of beliefs takes place at the level of an individual.) In addition to being interested in the robustness of the dynamics with respect to two different learning paradigms, we employ a model of individual learning as it is better suited for direct mapping into the design

[1] Models that incorporate imperfect and asymmetric information can give rise to one-time speculative attacks, but cannot generate recurrent currency crises.

[2] See, for example, Cole and Kehoe (1996, 2000), Jeanne and Masson (2000).

of the experiments with human subjects.

We simulate both models of social and individual learning for a large number of different parameter values, and examine the observed dynamics. It is noteworthy that the model of individual learning is also characterized by recurrent currency crises. Other features such as duration of periods of devaluation and no-devaluation and the characteristics of the times series of the models' variables that are generated vary across different types of simulations.

As the appropriate data regarding investors' beliefs is not available, the approach we take in this paper is to test the model's predictions in simulations with the data collected in the experiments with human subjects. This way we can directly observe the evolution of investors' beliefs over time and compare the properties of the distributions generated in a model and those that result from the experiments with human subjects. The observed experimental behavior matches well the behavior of the boundedly rational, artificial agents along many dimensions. Most importantly, experiments do result in recurrent instances of currency crises. We also examine the time series properties of the returns, both those generated by our model and those collected in the experiments. Both time series are characterized by 'fat tails' which is the feature observed in the real data on returns from the emerging markets (see Masson, 2003).

In section 2, we first describe a simple balance of payments model with a representative agent and characterize its rational expectations equilibrium. This description is followed by an introduction of a model in which agents have heterogenous beliefs. We present our two models of learning, social and individual, in section 3. We describe our simulation and experimental design in section 4. The results of simulations are presented in section 5. The analysis of the results of the experiments with human subjects and the features of the dynamics of the changes in expectations are discussed in section 6. Finally, concluding remarks are given in section 7.

2 A Model of Currency Crises

2.1 Representative agent model

We follow Arifovic and Masson (2003) in describing a simple model of a portfolio allocation between mature and emerging markets in which risk neutral investors decide to put their wealth either in an emerging market country or the United States. An emerging market central bank defends a currency peg using its foreign exchange reserves until those reserves reach some minimum value.

The U.S. asset is riskless, and pays a known rate r^*, while the emerging market asset's return, r_t, is subject to devaluation (or default) risk as well as potentially decreasing returns to the amount invested. The agent puts a fraction λ_t of her fixed wealth $\overline{W}$ in emerging market assets, such that expected returns on the two assets are equalized.

Making explicit the dependence of r_t on λ_t, letting π_t be the probability of a devaluation and δ_t the size of devaluation, the condition for portfolio equilibrium is[3]

$$r^* + \pi_t \delta^e = r_t = r(\lambda_t) \tag{1}$$

Inverting (1), we can write this dependence as

$$\lambda_t = \lambda(\pi_t) \tag{2}$$

[3]For convenience, cross product terms are ignored here.

As in the canonical currency crisis model (Krugman, 1979), devaluations are triggered by the decline of reserves to some threshold level, which we assume to be zero. The change in reserves is equal to the capital inflow plus the trade balance, minus the interest payments on outstanding debt:

$$R_t = R_{t-1} + T_t + D_t - D_{t-1} - r_{t-1}D_{t-1} \tag{3}$$

where $D_t = \lambda_t \overline{W}$. The trade balance T_t is stochastic and is assumed to follow a Markov process; that is, it depends only on its lagged value.

A rational expectation for the devaluation probability will satisfy

$$\pi_t = \Pr_t(R_{t+1} < 0 | no\ \ devaluation) \tag{4}$$

This probability can be rewritten

$$\pi_t = \Pr_t(R_t + T_{t+1} + \lambda(\pi_{t+1})\overline{W} - (1 + r^* + \pi_t \delta_t^e)\lambda(\pi_t)\overline{W} < 0) \tag{5}$$

Assuming that the reserve level R_t is part of the representative agent's information set, and using the notation in Jeanne and Masson (2000), we can write this as

$$\pi_t = \Pr_t(B(T_{t+1}, \pi_{t+1}, \pi_t) < 0 | T_t, R_t) \tag{6}$$

This latter equation determines the rational expectation for the devaluation probability, given the stochastic process for T_t.

The dynamics of (6) are difficult to characterize. However, it is shown in Jeanne and Masson that a simplified version of equation (6) can have multiple solutions. In particular, in the simplified case where B does not depend on π_t (just on π_{t+1})[4], nor on R_t, and if transitions between equilibria are described by a Markov transition matrix, then there is an unlimited number of rational expectations solutions. In particular, for any set of n equilibria, another rational expectations equilibrium can also be constructed.

2.2 A Simplified Model

Arifovic and Masson (2003) have shown that the model of social learning in which heterogenous beliefs about π_t, and δ_t that evolve over time results in recurrent currency crisis. In order to test the robustness of their model, they also examined the behavior of a simplified model in which only beliefs about π_t evolved, and the belief about δ_t was kept at the constant level. This model resulted in the same type of dynamics. Finally, a further simplification in which there is no stochastic element of the trade balance (resulting in $T_t = T_{t+1}$ for all t) did not affect the qualitative features of the dynamics. As the main objective of this paper is to compare the results of the simulations with the experimental data, we will work with this simplified model because it lends itself better to the experimental implementation.

Thus, we abstract from an evolving trade balance to one in which T_t equals zero for all periods. In addition, we assume that all individuals share the same expectation regarding the size of devaluation. Specifically, $\delta_{i,t}^e = \delta^e = 1$ for all i and over all periods t. In this simplified model, equilibrium

[4] The case where B depends on both π_{t+1} and π_t can generate chaotic dynamics, as shown in Jeanne and Masson (2000).

is no longer characterized by an infinite number of solutions. (The inclusion of a non-stochastic trade balance will instead decrease the number of rational expectation solutions to just two.)

Reserve levels are determined identically to the specification in equation (3), setting T_t equal to zero for all t.[5] The rational expectation solution for an individual's probability assessment is therefore still characterized by equation (5). We make the following assumption for the function $\lambda_t = \lambda(\pi_t)$

$$\lambda'(\pi_t) < 0 \tag{7}$$

ensuring that as individuals become more pessimistic, their investment in the emerging market decreases (ceteris paribus). We also assume $\lambda(0) = 1$ and $\lambda(\pi_{max}) = 0$. Under these simplifying assumptions, the rational expectations solution for π_t (equation (5)) therefore becomes

$$\pi_t = Pr_t(R_t + \lambda(\pi_t)\overline{W} - (1 + r^* + \pi_{t-1})\lambda(\pi_{t-1})\overline{W} < 0|no \quad devaluation) \tag{8}$$

In any situation in which $R_t > (1 + r^* + \pi_{t-1})\lambda(\pi_{t-1})\overline{W}$ holds, the solution to this assessment has a unique solution. Specifically, $\pi_t = 0$. Here, even as no funds are invested in the emerging market, it is impossible for a devaluation to occur. The reserve level of the emerging market's central bank is sufficient to cover *all* of its economy's current debt.

A unique solution also results in any situation in which it is impossible to meet a shortfall in reserves with incoming emerging market investment. That is, when $(1+r^*+\pi_{t-1})\lambda(\pi_{t-1})\overline{W} - R_t > \overline{W} > 0$ holds, a devaluation is certain, and $\pi_t = \pi_{max}$ is the unique solution.

Multiple solutions exist for situations that fall between these two extremes. That is, when incoming emerging market investment can meet reserve shortfalls, or when $\overline{W} > (1+r^*+\pi_{t-1})\lambda(\pi_{t-1})\overline{W} - R_t > 0$ holds, there are two possible solutions for π_t: $\pi_t = 0$ and $\pi_t = \pi_{max}$. It is impossible, without further specification, to select one of these solutions over the other. When π_t takes the value of π_{max}, a self-fulfilling devaluation takes place in which $\lambda(\pi_t = \pi_{max}) = 0$ and through a devaluation of currency, $R_{t+1} = 0$.[6]

In the period following this devaluation, the above problem simplifies to the following

$$\pi_t = Pr_t(R_{t+1} < 0) = Pr_t(\lambda(\pi_t)\overline{W} < 0) \tag{9}$$

As is the nature of self-fulfilling phenomena, when investors do not expect a devaluation, that is, when π_t takes the value of 0, a devaluation does not take place. Importantly, this cannot occur indefinitely, as interest payments on emerging market debt will slowly diminish the level of reserves available. Eventually, the economy will find itself with too few reserves to cover its interest outflow and a devaluation occurs.

All of the above analysis is based on a framework where a one-period model (stage game) is repeated over time. In this respect, agents really have expectations of probability of devaluation in

[5]Setting T_t equal to $\overline{T}$ rather than zero does not change the solutions' characterization in any significant manner

[6]This result is in essence a stag-hunt game with a payoff dominated equilibrium. In a model incorporating Bayesian learning, Chamely (2003) considers speculative attacks in a similar spirit. Agents update their expectations regarding the number of other agents that believe the current fundamentals are sufficient for a successful attack. Essentially, there are two states of the economy, one in which there is sufficient speculators for devaluation, and one in which there is not. The mass of these speculators is an uncertain parameter of this economy. While both models are essentially a game of timing, in Chamely's work multiple periods are necessary for the existence of speculative attacks and these attacks are not recurrent. However, the emphasis of Chamley's work is examining policies' ability to defend the currency peg, not in explaining recurrence.

the following period. However, if we assumed investors were forward looking, then their rationality will imply the logic of backward induction, i.e. in case that devaluation can occur in some period t, no investment in the emerging market will ever occur.

2.3 Heterogeneous agents

We now turn to the model with heterogeneous agents. There are n investors, each with constant wealth $\overline{W}$, who form expectations of the devaluation probability, π_t^i.[7] Since investors are risk neutral, they will be indifferent between investing in the two assets when their *ex ante* returns are equal, and choose between putting all their beginning-of-period wealth into the safe foreign asset, at rate r^*, or into emerging market claims, at rate r_t, depending on which expected return is greater.

We assume that each investor is a price taker, and does not influence the marginal product of capital in the emerging market economy. Short selling of either asset is ruled out; neither portfolio proportion can be negative.[8] If λ_t^i is the share of i's wealth in emerging market debt, then $\lambda_t^i = 0$ or 1 as $(1+r^*) >$ or $< (1+r_t)/(1+\pi_t^i)$.[9] Thus, at any period t, the amount of emerging market deposits held by all foreign investors is

$$D_t = \sum_{i=1}^{n} \lambda_t^i \overline{W}. \tag{10}$$

Emerging market banks set the interest rate on bank deposits to reflect market expectations of the return on emerging market debt. We assume that banks do not form expectations of devaluation themselves; they just use the average of all investors' expectations as a measure of the expected value of devaluation. Thus, the interest rate on emerging market deposits r_t is set equal to the U.S. rate plus a weighted average of the expected rate of devaluation. This equation, which is analogous to an interest parity (no arbitrage) condition, can be written

$$r_t = (1+r^*) \prod_{i=1}^{n} (1+\pi_t^i)^{1/n} - 1. \tag{11}$$

With different expectations, expected returns will be equalized only for the marginal investor whose expectation equals the average expectation. Each individual investor will make her investment choice on the basis of a comparison with the average expectation embodied in the interest rate. If she is more optimistic on emerging markets, in the sense of estimating a lower probability of devaluation than the average, then she will put all her wealth into emerging market debt; otherwise, she will put it all into U.S. assets. In this model, investor heterogeneity is key to determining the amount of emerging market assets held.

As in the above described representative agent model, a balance of payments identity relates the change in reserves to the trade balance (assumed for simplification to equal zero in all periods) plus the purchase of new debt by investors minus the principal and interest on maturing debt; assuming that there has been no devaluation or default:

[7] We continue to assume that each investor has an identical expectation regarding the devaluation size and that this expectation does not change over time, $\delta_t^{e,i} = \delta^e = 1$.

[8] Similar qualitative results can be obtained if borrowing is allowed, but there are limits on leverage (such as a minimum capital requirement).

[9] If the US rate were equal to the gross expected emerging market return discounted by the expected devaluation, λ_t^i would be indeterminate.

$$R_t = R_{t-1} + D_t - (1 + r_{t-1})D_{t-1}. \tag{12}$$

Reserves earn no interest, but they could just as easily have been assumed to earn r^*.

Provided that R_t is above some threshold level (which we assume without loss of generality to be zero), there is no devaluation at t, i.e. $\delta_t = 0$ (absence of superscript indicates that this is the realized value of depreciation, not its expectation). However, if reserves would otherwise be negative, there is a devaluation or default which reduces the amount that will be repaid on borrowing undertaken at t. That is, the ex post return for the lender will be $(1+r_t)/(1+\delta_t)$, where the amount of the devaluation is equal to the shortfall in the balance of payments that would have pushed R_t negative, divided by D_t:

$$\delta_t = \frac{-R_t}{D_t} \tag{13}$$

or using the above equation for R_t

$$\delta_t = \frac{[(1 + r_{t-1})D_{t-1} - R_{t-1} - D_t]}{D_t} \tag{14}$$

Though the devaluation/default reduces the amount owed at $t + 1$, not t, we assume that, in this case, balance of payments arrears are accumulated within the period such that reserves at t do not go negative but instead equal zero.

3 Evolution of Heterogenous Beliefs

Next, we describe the evolution of beliefs about probability of devaluation in the context of social and individual evolutionary learning.

3.1 Social Learning - A Baseline Model

We first describe Arifovic and Massson's model of *social learning* with boundedly rational agents who acquire the experience and knowledge needed to improve their performance over time. This model imposes weak requirements on agents' computational abilities. In this paper, the model of social learning will be referred to as our *baseline* model. The learning algorithm describes imitation-based adaptation of the agents' expectational rules (here a rule is just a point estimate for π_t^i. Investors consider their own success and that of other investors and try to imitate those rules yielding above-average returns. In addition, they occasionally experiment with new expectational rules.

Realized rates of return determine measures of performance of the expectations used at time t that we call *fitness* values. Performance, μ_t^i, of each investor's rule is evaluated based on the ex post return on emerging market assets

$$\mu_t^i = (1 + r_t)/(1 + \delta_t) - 1 \tag{15}$$

if investor i invested her wealth in the emerging market and to

$$\mu_t^i = r^* \tag{16}$$

if she invested in the US market. In the case that due to devaluation the performance value of an expectational rule takes a negative value ($\delta_t > r_t$), it is truncated to zero. Thus all the expectations that resulted in $\lambda_t^i = 1$ receive the same performance value even though they may have different values of π_t^i. Similarly, all those that resulted in $\lambda_t^i = 0$ receive the same performance value even though they may have different π_t^i's.

Investors update their expectations of π_t^i at the end of each period by imitating rules that have proven to be relatively successful and by occasional experimentation with new expectational rules. These two aspects of expectations formation are described below.

Imitation At the beginning of each period t, investor i, $i \in [1, \ldots, n]$ compares her expectational rule to a rule of a probabilistically selected investor j. The probability, Pr_t^j, that an expectational rule j is selected for comparison is equal to the expectational rule's relative performance:

$$Pr_t^j = \frac{\mu_t^j}{\sum_{i=1}^n \mu_t^i}. \tag{17}$$

We can think of the selection of an expectational rule j as resulting from a spin of a roulette wheel where each expectational rule is assigned a slot proportionate to its relative performance value (proportional selection). Rules that performed better get larger slots than rules that did worse in the previous period, and thus well-performing rules have higher probability of being selected. Rules are selected with replacement. Once j is selected, investor i compares the performance of her own expectational rule to the performance of investor j's expectational rule. If the performance of her own rule is equal or higher, she keeps her own rule. Otherwise, investor i imitates (adopts) the expectational rule of investor j.

Note that in case of devaluation, if $\delta_t > r_t$, expectational rules of the investors who invested in the emerging market yield a negative return, which is truncated to zero. Thus expectations of all investors who invested in the emerging market will receive performance values equal to 0 and will not be imitated. Only the expectations of those investors who invested in the US market receive positive, equal probabilities of being selected in this case.

Imitation alone represents a type of herd behavior in that on average, over time, well-performing expectations will be imitated (followed) by a larger number of investors and on average, investors will encounter better-performing expectations more frequently.

Experimentation Once the imitation is completed, each investor, $i \in [1, ..., n]$, can experiment with her expectational rule. Experimentation takes place with probability p_{ex}. If the investor experiments with the expected probability of devaluation, a new expected probability of devaluation is determined by drawing a random number from the uniform distribution over the interval $[0, \pi_{max}]$.

The above describes the framework which is assumed to govern the interaction of the population of investors. If investors are not able to gather enough information to form reliable estimates of the future behavior of the markets, and based on that determine their optimal behavior, imitation of previously successful strategies seems a plausible behavioral assumption. This type of behavior is explicitly modeled in our framework using proportional selection such that expectational rules that yielded an above-average payoff tend to be used by more investors in the following period. Experimentation incorporates innovations by investors, done either on purpose or by chance.

3.2 Individual Evolutionary Learning - An Extended Model

Next we combine the currency crisis framework of Arifovic and Masson with the model of individual evolutionary learning used by Arifovic and Ledyard (2003). We describe the model and the way we are going to implement it in our simulations.

3.2.1 Agent behavior

At the beginning of period t, each investor, i, has a collection A_t^i of possible alternative expectational rules. Each expectational rule of investor i is given by a real number that represents $\pi_{j,t}^i$ at time t. A_t^i consists of J alternatives, $a_{j,t}^i$, for $j \in \{1, \ldots, J\}$.[10] At each t, an investor selects an alternative randomly from A_t^i using a probability density Π_t^i on A_t^i.[11] This alternative then becomes the expectational rule that agent implements at time period t. We construct the initial set A_1^i by randomly selecting, with replacement, J expectational rules from the set of all possible rules within a predefined range. We construct the initial probability Π_1^i by letting $\Pi_1^i(a_{j,1}^i) = 1/J$.

After each investor chooses her expectational rule, we compute the emerging market interest rate, r_t. The next step is to determine the value of each investor's $\lambda_i(t)$. This is accomplished in the same manner as has already been described in the previous section. We use the rest of the model's equations to compute the level of reserves in the emerging market and extent of possible devaluation.

Based on the information obtained at t, each investor updates her collection of alternative expectational rules. This process consists of three pieces, computing foregone return, and performing experimentation and replication.

3.2.2 Foregone return

In updating A_t^i and Π_t^i, the first step is to calculate what we call *foregone* returns for each alternative expectational rule in the collection. This is the (expected) return, given the information at t, that the alternative $a_{j,t}^i$ would have received if it had been actually used, taking the behavior of other investors as given. We use the notation $r^i(a_j^i|s_t^i)$ to compute the hypothetical return of the alternative j that belongs to investor i's set of alternatives.

For each alternative j, we determine the value of hypothetical $\lambda_{j,t}^i$, given the value of $\pi_{j,t}^i$. Finally, using this value of $\lambda_{j,t}^i$, we compute the rules' foregone return. In this model, this represents their performance measure.

3.2.3 Updating A_t^i

We modify A_t^i with processes of experimentation and imitation analogous to the ones described above for social learning. Foregone returns play the role of fitness values. The process of imitation results in the increase in frequency of the better performing rules. In case of our extended model, it can be interpreted as a reinforcement of those expectational rules that resulted in higher foregone returns.

While algorithmically the process of experimentation is performed the same way in the two models, it has different interpretation and impact on the dynamics. In the baseline model (social

[10] J is a free parameter of the behavioral model that can be varied in the simulations. It can be loosely thought of as a measure of the processing and/or memory capacity of the agent.

[11] In essence the pair (A_t^i,Π_t^i) is a mixed strategy for i at t.

learning) it is a trembling hand random mutation. However, in the extended model (individual learning), newly generated rules will not be automatically tried out when they are generated. They have first to increase their frequency, based on high foregone payoffs, in order increase their probability of actually being selected.

We refer to the above described model of individual evolutionary learning as our *extended* model in the subsequent analysis.[12]

4 Design of Simulations and Experiments with Human Subjects

4.1 Simulations

As mentioned earlier, we focus here on simulations in which δ_t^e is *not* allowed to evolve. This algorithm is referred to as the fixed - δ^e case by Arifovic and Masson. Here, the expectational rule is characterized by a single real number, π_t^i (the probability of devaluation), and it is assumed that the expected amount of devaluation, $\delta_t^{e,i}$, is equal across investors and time.

Agents (n) and Experimentation Rates (p_{ex}) We first simulate permutations over the rate of experimentation and number of agents for the baseline simulation (one rule per agent). Holding the experimentation rates at 0.33, 0.165, 0.0825, and 0.04 we simulate over population levels that include 100, 75, 50, 25, and 12. As total wealth remains constant throughout these simulations ($\overline{W}$), decreasing the number of agents has the effect of increasing the per period investment of each individual. Decreasing the experimentation rate has the effect of decreasing the amount of heterogeneity introduced in each period.

Strategy Set Size - J In the model of learning in which agents have a set of alternative rules played probabilistically (A_t^i, Π_t^i), we simulate various permutations over the size of this strategy set J. We allow the strategy set size, J, to equal 45, 15, and 5. For each parameterization of J, we simulate over the various permutations of population levels according to 100, 75, 50, 25, and 12, and of experimentation rates according to 0.0825, and 0.04.

Simulations over very low specifications of the population of agents, $n = 12$, are used to gauge the impact of lower population levels on the simulations' dynamics. These are used in order to facilitate a comparison to experimental data where, due to constraints, population levels are below that which would be considered appropriate to approximate perfect competition. However, these levels may not be sufficient for ensuring the efficacy of the learning algorithm as diversity over rules reaches a critically low level. This is a concern, foremost, for social learning where diversity is a direct function of population levels. This direct relationship is not a characteristic of individual learning, as J allows for a break between the direct relationship between population and diversity over rules. For this reason we expect, *a priori*, the results of the low population individual learning parameterization of the model to be more rhobust with respect to decreases in the population and therefore offer a more favorable comparison with experimental data. Additionally, social learning

[12]Individual and social learning can be complimentary. It is feasible to incorporate both types of learning within a single model of adaptation. A model of individual learning can incorporate imitation *across* individual sets of J rules. This intra-individual imitation, occurring between randomly chosen pairs of individuals every t_i periods, allows individuals to mimic the strategies of other agents utilizing a fitness (payoff) criterion in order to determine the relative success of the two sets of rules. An individual imitates the other pair's rules if, and only if, this criterion is met.

entails knowledge of other individuals' rules which will not be a feature within the experimental environment.

Risk Averse Agents - b_i We extend the model of the portfolio choice of agents to one that includes a specification of risk averse investors. The equation that determines investment in the emerging market, as derived by Masson (2003), is

$$\lambda_t^i = \frac{b^i(r_t - \pi_t^i \delta_t^i - r^*)}{\pi_t^i(1-\pi_t^i)(\delta_t^i)^2} \tag{18}$$

where, λ_t^i is set to unity if the above equation yields a result strictly greater than one, and zero if strictly less than zero. Here, b_i is a utility parameter negatively related to the degree of risk aversion of the particular investor. Risk neutrality is equivalent to setting this parameter to infinity. Each agent has the same measure of risk aversion ($b_i = b \ \forall \ i \in [1 \ldots n]$).

We maintain a parameterization of b_i equal to 1 and simulate the baseline model of expectations including the four population levels described above (100, 75, 50, 25, 12) and an experimentation rate equal to 0.0825. Using these parameterizations of population and exerimentation, the extended model incorporating b_i is simulated with 15 rules per agent.

Parameterization of Simulations As described above, the permutations over n, p_{ex}, J, and b_i include a total of 60 unique parameterizations of the simulations. All of the results of these simulations are presented in the Appendix.

4.2 Experiments with Human Subjects

Our experimental design follows closely that of our extended simulation design in which δ_t^i is equal to one for all investors and over all experimental periods.[13]

Subjects were economics SFU undergraduates, third and fourth year. They volunteered, i.e. none were participating for fulfillment of any course requirement, and were paid a "show-up" fee and awarded an additional payment dependent on performance.[14] We used Z-tree software for experimental economics developed by Urs Fischbacher to create our experimental environment.

Initial Conditions - Instructions Prior to the beginning of an experiment, subjects are given the following information: (1) the balance of payments identity that governs the currency reserves of the emerging economy's central bank in the following period; (2) the equation determining the rate of return in the emerging economy's asset market; (3) the fixed rate of return in the U.S. economy, r^*, and an initial value of the emerging market rate of return, r_0; (4) the initial level of investment in the emerging market, D_0; (5) The constant wealth available for investment, $\overline{W}$ in each period; (6) the equation governing their portfolio allocation; (7) and the method according to which experimental payoff is determined. This information is contained in a set of instructions

[13] An alternative experimental design may be found in the work of Heinemann, Nagel and Ockenfels (2004). Their work tests the predictions of global game theory with respect to private information using a reduced form Morris and Shin (1998) model. However, as consecutive experimental periods are in no way related in terms of fundamentals, the work cannot focus on the recurrence or duration of devaluation and no-devaluation periods.

[14] The "show-up" fee was equal to 15 dollars. The performance dependent payment was calculated in a manner such that the average total payment across subjects amounted to approximately 25 dollars. Subjects were informed about the nature of the total payment prior to participation in the experiment.

read by, and to, participants of the experiment. Each experimental period proceeds in the following way:

Subjects' Assessment of π_t^i At the beginning of each period, subjects are asked to quantify the probability of devaluation. At any time may subjects view the report of variables described in the previous section or the *experiment parameters* and the history of relevant variables. Experimental subjects are prompted for their assessment of the probability of devaluation. In order to make this assessment more intuitive, they are asked to enter a probability over the span of $[0, 10]$ rather than $[0, .10] = [0, \pi_{max}]$. Their assessment is then converted to a $\pi_t^{e,i}$ by dividing by 100.[15] The rest of the calculations are performed following the equation presented earlier.[16]

Report of Results Subjects are shown their resulting portfolio and rate of return, and their experimental payoff for that period. Subjects are also informed of that periods' *ex ante* and *ex post* rates of return in the emerging market (before and after any devaluation, r_t, δ_t and $(1+r_t)/(1+\delta_t)$), and of the total level of investment in the emerging market from the previous period, D_{t-1}.

Treatment Payoffs A per period payoff for each subject is based on earnings in excess of the per period investment. That is, a subject earns $r^* \frac{\overline{W}}{n}$ when invested in the domestic market, $r_t \frac{\overline{W}}{n}$ when invested in the emerging market, and $[(1 + r_t)/(1 + \delta_t) - 1] \frac{\overline{W}}{n}$ when invested in the emerging market in periods in which a devaluation takes place. Wealth, $\overline{W}$, is not accumulating; each subject has the opportunity to invest a constant amount in each period that is not dependent on previous investment performance. Importantly, as was the case in the simulations' fitness functions, experimental profit is bounded below by zero. Cumulative experimental profit translates into cash payment via a conversion factor. Total payment to the subject is the sum of a "show-up fee" and the converted experimental profit.

Experimental subjects' information set It is important to emphasize which variables are in the participants' information set and which are excluded. Each participant knows the complete history of total foreign investment, the *ex ante* and *ex post* emerging market return, and the extent of devaluation. However, they do not have information on the following: (i) the current level of currency reserves of the emerging market's central bank, and (ii) the devaluation threshold. We assume that in reality, although reserve levels may be known by investors, the threshold under which devaluation occurs is unknown. We remove knowledge regarding the current level of reserves in order to avoid subjects' learning the devaluation threshold through repeated observation of devaluations.

[15]The parameterization of π_{max} is taken from the original work of Arifovic and Masson (2003) in order to maintain comparability of results. It's original specification was in order to align simulations' interest rate spreads with those of monthly emerging market data.

[16]Under the unlikely scenario that a subject's assessment equals the geometric mean of all assessments, the subject's wealth is invested wholly in the emerging market if $\pi_t^i < \pi_{max}/2$, wholly in the domestic market if $\pi_t^i > \pi_{max}/2$, and split equally between the emerging and domestic markets if $\pi_t^i = \pi_{max}/2$. However, these rules did not have to be implemented in any of the sessions.

5 Simulation Results

Initial Values The values of initial external debt, and reserves, US interest rate, as well as the value of total wealth were taken from Arifovic and Masson (2003). Thus, the initial values for external debt, and reserves were taken to be those prevailing in Argentina at the end of 1996. In these "fixed - δ^e" simulations, the trade balance does *not* evolve. Interest rates and flows are converted to monthly data. All stocks and flows are expressed as ratios to GDP, so the relevant interest rates are actually the difference between the nominal interest rate and the growth of nominal GDP. For r^*, the U.S. interest rate used was $(0.05-0.03)$, or 0.001666. Variables of interest include

$$D_1 = 412.8, R_1 = 73.2, T_1 = -0.3, n\overline{W} = 825.6 \tag{19}$$

where the value for total wealth, $n\overline{W}$, was arbitrarily chosen to be twice D_1, π_{max} was chosen as 0.1, and $\delta^e_{max} = \delta^{e,i}_t = 1$.

5.1 Spread Statistics

Masson (2003) studies empirical regularities within the returns on emerging market debt.[17] The data indicate that daily changes in spreads are definitely not normally distributed, exhibiting much fatter tails. The study also finds generally significant first-order autocorrelation coefficient.[18] Our intention is to compare our simulation and experimental results to these two regularities. It is worth emphasizing that these results are derived from daily (not monthly) observations.

First Difference in Interest Rate Spread
Summary Statistics - Masson (2003)

Standard Deviation	0.04832
Skewness	-0.305
Kurtosis	86.06
Jarque-Bera	8,004,456
Observations	27,842
AC(1) (EMBI+)	0.134

Table 1: First Difference in Interest Rate Spread - Summary Statistics - Masson (2003)

[17] He uses a set of spreads on emerging market debt compiled by JP Morgan using daily data from 31 December 1993 to 19 July 2002. This data base comprises virtually the universe of all developing countries issuing Brady bonds and Eurobonds. The list of countries is the following (those included in JP Morgan's so-called EMBI+ index, see JP Morgan, 1995): Argentina, Brazil, Bulgaria, Colombia, Ecuador, Korea, Mexico, Morocco, Panama, Peru, Philippines, Poland, Qatar, Russia, South Africa, Turkey, Ukraine, and Venezuela. However, not all countries had bonds outstanding during the whole period 1993-2002; what observations existed were pooled to study the distribution of spreads.

[18] Masson notes that this could be due to market inefficiencies that allow arbitrage opportunities to exist, or could reflect lack of trading so that spreads quoted do not correspond to actual transactions.

In Table 3, 4 and 5 of the Appendix, we include distribution statistics for the first difference in the emerging market's interest rate spread, $[(1 + r_t)/(1 + \delta_t) - (1 + r^*)]$. We will compare the qualitative features of these distributions to those of Masson (2003).[19]

Standard Deviation - Second Moment The standard deviation of the first difference in interest rate spreads vary between permutations of the simulations. However, all simulations' standard deviation fall in the $[0.0242, 0.0982]$ range. It is somewhat striking that even for parameterizations originally considered extreme, the standard deviation falls in this relatively small range. Notably, in the baseline simulations (simulations 1 through 20), decreasing the population level has the effect of increasing this measured standard deviation.

Skewness - Third Moment From the distribution of the first difference in the emerging market interest rate spread for each permutation, we calculate the measure of skewness. In all of the simulations, the skewness statistic from this distribution measures positive falling on the range $[0.0742, 1.6117]$; this result does not appear to align itself well with the empirical findings based on daily data.

Kurtosis - Fourth Moment From the distribution of the first difference in the emerging market interest rate spread for each permutation, we calculate the measure of Kurtosis according to the following equation:

$$K = (\frac{1}{N})\Sigma_{i=1}^{N}(\frac{y_i - \overline{y}}{\widehat{\sigma}})^4 \tag{20}$$

Distributions with a kurtosis measure of 3 are referred to as mesokurtic, of which the normal distribution is a prime example. Those distributions with a kurtosis measure exceeding 3 are referred to as leptokurtic, and are characterized by slim or long-tails. Finally, those distributions with a kurtosis measure less than 3 are referred to as platykurtic (fat or short-tailed). Masson (2003) finds a high value of kurtosis over daily first difference in interest rate spreads. Over all data sets that they consider, this measure is in excess of 80. In most of our permutations, the kurtosis measure far exceeds that of a normal distribution, reaching a maximum of approximately 56 in the baseline simulation with 100 agents, experimentation with probability 0.0825, and with a risk aversion parameter equal to 1 (simulation number 96).

Although the values of kurtosis computed in our simulations do not reach the empirical measure of around 80, the measures are in excess of that associated with normal distribution (with the exception of three parameterizations).[20]

Jarque-Bera The normal distribution has a skewness and kurtosis measure of zero and three respectively. A simple test of normality is to find whether the computed values of skewness and

[19] The data presented in the Appendix to this chapter represents a subset of 120 different parameterizations of the simulations. For brevity and parsimony, we exclude presenting parameterizations that yield results redundant to those considered herein. Distinct parameterizations within the population of simulations are associated with unique simulation numbers. Therein, the non-sequential numbering of simulations in the Appendix has been maintained to facilitate comparison with the entire sample utilized in other work.

[20] Parameterizations that do not have Kurtosis measures in excess of 3 are contained in simulations 77 through 79, inclusive.

kurtosis depart from the norms of 0 and 3. This is the logic behind the Jarque-Bera (JB) test of normality.

$$JB = N[\frac{S^2}{6} + \frac{[K-3]^2}{24}] \tag{21}$$

Where S refers to skewness and K, kurtosis. Under the null hypothesis of normality, JB is distributed as a Chi-square statistic with 2 degrees of freedom.

According to Masson (2003), daily change in spreads occur over a non-normal distribution. In all of our 60 permutations of the model, we reject the null hypothesis of normality using the Jarque-Bera test.

Autocorrelation Coefficients We report the estimates of the first order autocorrelation coefficient from an autoregressive regression including the first difference in spread measures in Tables 3 through 5. The estimated first order autocorrelation coefficient is significantly negative in all of our simulations. This contrasts the positive correlation reported in Masson (2003). However, it is important to note that the positive correlation in Masson 's work is over daily changes in interest rate spreads, rather than the monthly changes expressed in the simulations of this paper. It is quite likely that the monthly first difference in spreads are negatively correlated empirically, while daily are positively; a result very common to financial data. However, this conjecture requires validation using data not available at this time.

Summary Overall, the regularities of the spread statistics are extremely robust over the permutations of the parameter choices of the simulations, both baseline and extended. The most important finding is the robustness *across* the models of learning. In sum, regardless of the choice of model and for its parameterization, the distribution of the first difference in interest rate spread is positively skewed with a Kurtosis measure well in excess of the normal and the interest rate spread is negatively autocorrelated. Although falling short of matching empirical data with respect to skewness and first order autocorrelation coefficients, standard deviation and kurtosis measures capture empirical regularities well.[21]

5.2 Duration Statistics over Parameter Permutations

The Baseline Model - Comparison with Arifovic and Masson (2003) In our simulations of the baseline model, the observed dynamics are identical to those reported by Arifovic and Masson. The model exhibits recurrent instances of devaluations. We now consider the average duration of devaluation and no-devaluation periods over the various permutations of parameter specifications, using our two models of learning. In each simulation, the baseline initial values described above are used.[22]

Tables 6 and 7 present the average duration of periods of devaluation and non-devaluation for each of the simulations. We differentiate between two definitions of devaluation. Our first definition corresponds to the standard definition of devaluation (the same was used in Arifovic and Masson). That is, a simulation is within a period of devaluation if δ_t is greater than zero (or, anytime

[21]However, we would like to point out that this comparison is made with qualification. The measures of kurtosis and skewness reported in Masson (2003) are those of daily data, while in our simulations, the generated data refers to monthly intervals.

[22]As in Arifovic and Masson, each simulation is run for $10,000$ periods.

reserves fall below their the threshold value). We refer to these as simply *devaluations*. They occur whenever the emerging market's currency undergoes a depreciation against the domestic. The *ex post* emerging rate of return is lower than *ex ante* rate of return.

However, the fact that the emerging market's currency depreciated does not guarantee that the resulting rate of return earned from investing in the emerging market is lower than that of investing in the domestic market. A depreciation arising from reserves shortages may not be enough to make investing in the domestic market more attractive. Therefore, we also include a definition of devaluation periods that only include those in which the *ex post* rate of return in the emerging market is strictly lower than that of the domestic. We refer to these periods as *dynamically relevant devaluations*.

Why is this distinction important? The answer is related to the evaluation of the payoff (fitness) function used in the simulations and experiments with human subjects. Although a devaluation may have occurred in the previous simulation period, if it was not large enough to drive the *ex post* emerging market return below that of the domestic market, rules that translated into investment in the emerging market will propagate. Therefore, simulation dynamics are more likely to be based on the dynamically relevant devaluations rather than the standard definition of devaluation. We discuss the results across different types of simulations.

Baseline Simulations First, consider the baseline simulations (simulations 1 through 20). Consistent with the results of Arifovic and Masson (2003), holding the numbers of investors constant, decreasing the rate of experimentation (p_{ex}) decreases the average duration of periods of devaluation. Upon the onset of a devaluation, those investment rules associated with domestic investment earn higher rates of return than those associated with investment in the emerging economy. For a devaluation to continue, investment must favor the domestic market, therein pulling wealth out of the emerging economy. This occurs when those rules associated with domestic investment are imitated by investors; a process that is inherent in the social learning algorithm. However, with higher rates of experimentation, this imitation is not as effective and the favoring of the domestic economy is less prominent. Increased experimentation decreases the ability of imitation and therefore the swing towards domestic investment required for sustained devaluations is less probable.

Additionally, holding the rate of experimentation constant, lowering the population levels of the baseline simulations tends to decrease the average duration of periods of devaluation. However, this result does not hold for the two lowest specifications of p_{ex} where the duration measures for these parameterizations are already near their lower bound. As such, no decrease in the duration of devaluations is possible. This holds as well when considering periods without devaluations. Generally, decreasing the number of investors in the baseline simulation (ceteris paribus) has the effect of lowering durations of both devaluation and no-devaluation periods.

Extended Simulations Our extended simulations of individual evolutionary learning result in shorter duration of no-devaluation periods when the size of agents' collections of alternative rules is relatively small. In these simulations, we observe a more frequent switching between states of devaluation and those with no devaluation. Specifically, extended simulations in which agents have a collection of five rules and experimentation rates equal to 0.04 (simulations 76 through 80, inclusive) have average durations of successive periods without devaluation two to three times smaller than their baseline counterparts (simulations 16 through 20). This result holds across both specifications of the experimentation rate.

This decrease in duration measures from the baseline model does not hold when the number of rules in the investors' collections increases to it's largest specification ($J = 45$, simulations 61 through 65). Here, duration measures for no-devaluation periods are very comparable to the baseline model counterparts.

We conclude that decreasing the diversity of rules available for each agent is very important for decreasing the duration of of no-devaluation periods.[23] Smaller collections of rules are associated with shorter periods without devaluations.

Decreasing the size of each agent's collection has the effect of increasing the duration of devaluation periods. For both specifications of p_{ex}, the duration of devaluations is longest with the lowest specification of the number of rules in this collection (and with the number of investors, n equal to 100).

Holding the number of rules per agent and the rate of experimentation constant, decreasing the number of agents has the effect of lowering both the duration of devaluation and no-devaluation periods (consistent with the baseline results).

Decreasing the experimentation rate does not seem to have any general effects in the extended simulations with high numbers of rules in agents' subsets. However, when these subsets are quite low (5 rules), lowering the experimentation rate decreases the duration of devaluation and no-devaluation periods.

One could argue that some of the relatively smaller average durations of devaluation periods under the extended model of learning are empirically unrealistic. However, when we consider the simulations' duration statistics in light of our experimental data, these lower no-devaluation durations must be considered a success.

Risk Aversion - Baseline and Extended Model From the consideration of risk neutrality, we incorporate risk aversion by decreasing the risk aversion parameter (b_i) to a value of one.

Consistent with the conclusions for the baseline and extended simulations considered above, with risk aversion included in simulations, decreasing the number of agents (ceteris paribus) lowers both devaluation and no-devaluation duration measures.

In the baseline model, holding all parameters constant and decreasing the risk aversion parameter tends to increase the duration of devaluation and no-devaluation periods for simulations with larger numbers of agents (100, 75 and 50). For simulations in which the population is at one of its lowest two specifications, 12 and 25, decreasing the measure of risk aversion decreases the duration of no-devaluation periods considerably (duration measures for devaluation periods are already near their lower bound for these levels).

Decreasing the risk aversion parameter in the extended model increases both the duration of devaluation and no-devaluation periods at all population levels.

5.3 Average Assessment (π_t^i) - Regression Analysis

Stylized facts regarding interest rate spreads leading up to and following currency devaluations are considered in the work of Tornell and Westermann (2001). In the consideration within this work, it is observed that interest rate spreads tend to increase in the period immediately preceding the onset of devaluation. This increase is estimated to be one percent. It is followed by a further

[23] Note that decreasing the number of agents in the baseline model would have the same effect on diversity. As described above, the resulting impact on duration statistics is the same.

increase in the period of devaluation of three and a half percent; a total increase of four and a half percent is observed leading up to currency devaluations. Following the onset of the devaluation, interest rate spreads tend to decrease.

This decrease in the interest rate spread following devaluation is considered in the recent work of Kasa and Cho (2003). Their work is motivated toward explaining the recession that appears to follow periods of currency devaluation. While third generation models of currency crises accounted for this observation through their inclusion of "balance sheet effects", currency crises are still the result of exogenous sunspot affects. Their application of a model of learning and adaptation to the beliefs of the policy-maker and the agents makes endogenous the onset of crises; the onset of currency crises may be linked to the stochastic properties of their model of learning and the structural features of the economy.[24] The fall in the interest rate spread may result from a mix of both risk premium effects and loose monetary policy. As noted by Kasa and Cho (2003), this loose monetary policy may be a concerted attempt to avoid the recession that follows devaluation. Of course, this policy tends to worsen the crises, deepening the impact of the initial devaluation of the value of the currency.

Our test on the first difference in interest rate spreads is related only to changes resulting from the increases of decreases in the risk premium. We attempt to find changes in this spread, derived from changes in the premium, that are not predicted by the change in the preceding period. Tables 8 through 14 include regressions on the first difference in average assessment ($\overline{\pi_t}$). There is no constant term included in these estimations. We include six explanatory variables, including the first lag of difference in average assessment, and five dummy variables in two regressions per simulation. Each dummy controls for specific periods within the simulations. The details of our analysis are contained within Table 2.

Specification of Dummy Variables	
$D1$	$\delta_t = 0$ and $\delta_{t+1} > 0$
$D2$	$\delta_t > 0$ and $\delta_{t-1} = 0$
$D3$	$\delta_{t-1} > 0$ and $\delta_{t-2} = 0$
$D4$	$\delta_t = 0$ and $\delta_{t-1} > 0$
$D5$	$\delta_{t-1} = 0$ and $\delta_{t-2} > 0$
$D6$	$r_t - \delta_t \geq r^*$ and $r_{t+1} - \delta_{t+1} < r^*$
$D7$	$r_t - \delta_t < r^*$ and $r_{t-1} - \delta_{t-1} \geq r^*$
$D8$	$r_{t-1} - \delta_{t-1} < r^*$ and $r_{t-2} - \delta_{t-2} \geq r^*$
$D9$	$r_t - \delta_t \geq r^*$ and $r_{t-1} - \delta_{t-1} < r^*$
$D10$	$r_{t-1} - \delta_{t-1} \geq r^*$ and $r_{t-2} - \delta_{t-2} < r^*$

Table 2: Specification of Dummy Variables - Regression Analysis

We use $r_t - \delta_t$ as an approximation for $[(1 + r_t)/(1 + \delta_t) - 1]$. We can interpret the estimated

[24]Notably, in the model considered herein, currency crises are also linked to the model of learning. However, as discussed above, currency crises are only a result of this adaptation on the part of agents; not to the economic fundamentals of the emerging economy.

coefficient on a dummy variable as the change in $\overline{\pi_t}$ in simulation periods with the characteristics as described in the above that is not explained with the lagged difference in $\overline{\pi_t}$. The dummy variables numbered one through five are associated with the standard definition of devaluations, and those numbered six through ten are associated with the stricter definition of dynamically relevant devaluation.

Our results for changes preceding devaluations coincide with that observed empirically. In the majority of parameterizations of the simulation, the period preceding the onset of a devaluation is characterized by a higher than expected interest rate spread. Evidence is found in the positive coefficient estimate of the $D6$ dummy variable. However, in the period in which a devaluation begins, $D7$, interest rate spreads are lower than would otherwise be predicted. Importantly, this measured effect is stronger than that inherent in the period preceding devaluation. As the lag of the first difference in interest rate spread has an estimated coefficient that is always less than one we may also conclude that there is an absolute fall in the interest rate spread these periods. This result stands in contrast to the data summarized by Tornwell and Westermann (2001).

Importantly, Kasa and Cho (2003) also find it difficult to model increases in the interest rate spread in the onset period of devaluation. Their conjecture is that policy makers "lose control" of a mild depreciation attempt.[25] In contrast, the fall in the spread we witness stems solely from a fall in the mean investor sentiment regarding the likelihood of devaluation. Similarly, although following the onset of a period of devaluation we witness a very strong increase in the interest rate spread, $D8$, this effect is reflective of only an increase in the risk premium in isolation. Our model does not incorporate the potential of expansive monetary policy in an effort to alleviate economic recession.

6 Experimental Results and the Dynamics of Expectations

In this section we compare the results of our simulations to those obtained in the experiments with human subjects. We conducted a total of three experimental sessions. [26] We had 15 subjects in our first experimental session, and 11 subjects in the last two experimental sessions. The summary statistics are presented in Tables 5, 7 and 15.

In all experimental sessions we observe negative correlation between the first difference in spread statistics, kurtosis measures greater than that associated with the normal distribution, and positive skewness. These regularities match the simulations very well. In the sessions with 11 subjects, standard deviation measures are slightly larger than those of the session with 15 subjects. We noted above that smaller number of agents in the baseline simulations yielded larger standard deviation measures. The 15 subject session has a standard deviation measure within the range of those associated with the simulations. Kurtosis measures for all of the sessions fall within the range of those for the various permutations of the simulations.

The average duration of periods of devaluation and periods with no-devaluation are generally quite small when compared to those of the baseline Arifovic/Masson simulations (simulations 1, 6, 11, and 16). Although we conducted only one session with 15 subjects, it is noteworthy that the treatment with a larger number of subjects also has larger durations of devaluation and no-

[25] As noted by Kasa and Cho (2003), an empirical counterpart to this conjecture may be found in Britain's departure from the EMS following the September 1992 attack; interpreted as allowing Britain to embark on a policy of lower interest rates

[26] We set π_{max} 0.10 to match the number used in our simulations.

devaluation periods. These are not unexpected outcomes. Our discussion above refers to falling durations for specifications with a smaller number of agents; though these smaller durations are still larger than those of the treatments, especially with respect to no-devaluation periods. When we allow for smaller number of agents, the baseline simulations reasonably approximate the experimental results.

We have also noted that the simulations of our extended, individual learning model are sometimes associated with far more switching between devaluation and no-devaluation states. A final point with respect to durations is that simulations of the extended model match the experimental data very well. Consider, for example, simulation number 80: an extended, individual learning model with 12 agents, 5 rules each and an experimentation rate of 0.04. Its duration measures of 2.07 and 4.83 match the 11 subject sessions quite well with respect to duration of devaluation and no-devaluation periods, respectively. Similarly, simulations with slightly larger collections of rules (15 rules per agent, simulations 71 through 75) perform well in matching the 15 subject session.

We now turn to the analysis of the behavior of the average assessment of devaluation in experiments with human subjects and in simulations of our baseline and extended model. Figures 1 - 3 plot the average assessment of devaluation ($\overline{\pi_t}$) and devaluation size (δ_t) over time. Data for a subset of periods of a baseline and extended model simulations are given in Figures 1 and 2, respectively. The results of one of the experimental session are contained in Figure 3.[27]

A defining characteristic of the plots of the experimental average assessment is the relatively small range in which these measures fall when compared to those of the standard baseline simulations. For example, in the final ninety experimental periods of the session presented in Figure 3, average assessment is never larger than 0.05, and in only a very few periods does it fall below 0.02.[28] A similar lower bound exists for the plots associated with the standard baseline simulations. However, in the majority of periods of devaluation, the average assessment climbs as high as 0.08. One may argue that the baseline simulation and the experimental results share a common lower bound for average assessment. It is important to note that within experiments, there are many situations wherein the onset of a devaluation is not associated with an average assessment close to the lower bound. This is rarely the case for the baseline simulation results. Additionally, the upper bound placed on assessment does not appear relevant for reversing these periods of devaluation in treatments, as average assessment rarely crosses the 0.05 level.

The plots of the average assessment for our extended model look much more like experimental data. Consider Figure 2, plotting the extended model simulation's results. Here, the plot of average assessment looks very much like those plotted for the experimental session. Periods of devaluation are not necessarily associated with the lower bound on assessment, and the reversal of these devaluation periods occurs far before average assessment can climb to its upper boundary. In this respect, extended,individual learning simulations appear to match the experimental dynamics much better than the baseline specification.

The extended, individual evolutionary learning simulations compare more favorably to the ex-

[27]In order to facilitate comparison between simulation and experimental results, the following parameter choices are used for the baseline (Figure 1) and extended (Figure 2) simulation plots. The baseline simulation has 12 agents, one rule per agent, and a probability of experimentation set to 0.0825. The extended simulation is one in which 12 agents have 5 rules in their collections and experiment with a probability equal to 0.0825. Figure 3, that of the experimental data, is a session with 11 subjects.

[28]With respect to average assessment, the results of the other sessions are both qualitatively and quantitatively similar. Importantly, there is nothing particular to the specific experimental session we are discussing that cannot also be said of the other two sessions.

perimental results with respect to duration statistics. Specifically, they exhibit more frequent devaluation periods, and substantially shorter durations of no-devaluation periods. The range under which the average assessment occurs for the extended model simulations is quite smaller than that of the single-rule simulations. In addition to duration of devaluation and no-devaluation periods, this is a key characteristic the extended model simulations share with the experimental results.

Our examination of simulation and experimental data indicates that devaluations result from shifts in skewness of the distribution of $\pi_t^{e,i}$. Thus, the change of skewness plays crucial role in getting into periods of devaluation as well as getting out of them.[29] We estimate regressions over the time series of the first difference in average assessment. Included as independent variables is the first lag of differenced assessment, and the dummy variables specified above.

We define as sentiment reversal increases or decreases in average assessments that are *not otherwise predicted by the lag of the differenced assessment*. The estimated coefficients on the $D2, D4$ and $D7, D9$ dummy variables are reported in Table 8 through 15. The numbers show that there is quite some variation over the coefficient estimates across the different simulation permutations. There appears little consistency in the coefficient sign of the lagged difference in the assessment regressors. One thing to note is that in the simulations of the baseline model, both decreasing the rate of mutation, and decreasing the number of agents puts negative pressure on the $D2$ coefficient, often pushing it into negative territory.

7 Concluding Remarks

We study a model of currency crisis where the only source of volatility that contains potential for speculative attacks and devaluation of currency are agents' beliefs. The beliefs are heterogenous and evolve over time. We use two different frameworks, social learning and individual learning. As part of our methodology, we conduct a large number of simulations for different parameter values to check for the robustness of the results.

One of the striking results is that most of the main features of the dynamics are present for the whole range of different parameter values and over a wide range of specifications. These include the 'fat tails', positive skewness, and negative correlation between the first difference in spread statistics. The 'fat tails' is also a feature that characterizes empirical data on the returns in the emerging markets.

We also conducted three experimental sessions with human subjects where we simulated the same type of the economy. The features of the exhibited dynamics coincide with those of our simulations, i.e. fat tails, positive skewness, and negative correlation between the first difference in spread statistics. Regarding the duration of devaluation and no-devaluation periods, and the range of values within which the assessment of devaluation varies, our extended, individual learning model matches the experimental data well.

[29] The model requires shifts in the skewness of the distribution over individual assessments in order to obtain variation in the flow of investment. Therefore, shifts in skewness are required for devaluations. Importantly, shifts in skewness are not necessarily associated with shifts in the average assessment, utilized to determine the interest rate in the emerging economy. Therein, there is no theoretical link in this model between the shifts in skewness required for devaluations and changes in the interest rate spread associated with the average assessment. Importantly, skewness in the average assessment over individuals does not necessarily translate into skewness of the interest rate spread. The two have no theoretical relation in the model considered herein.

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8 Appendix

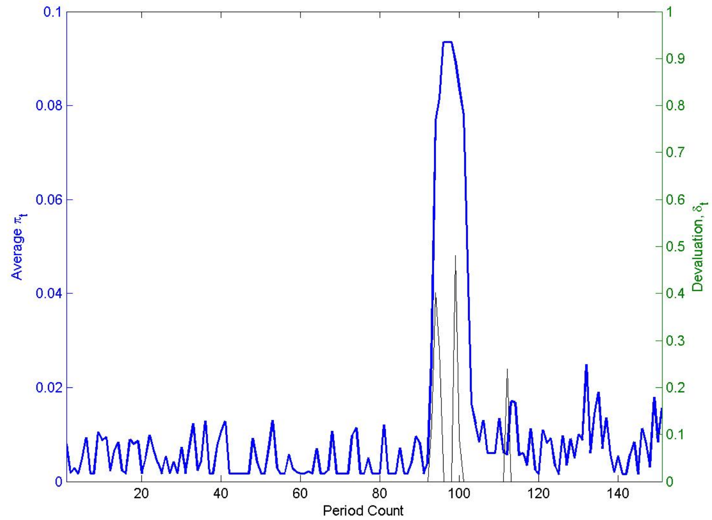

Figure 1: Baseline Simulation - 12 agents, 1 rule per agent, probability of mutation 0.0825

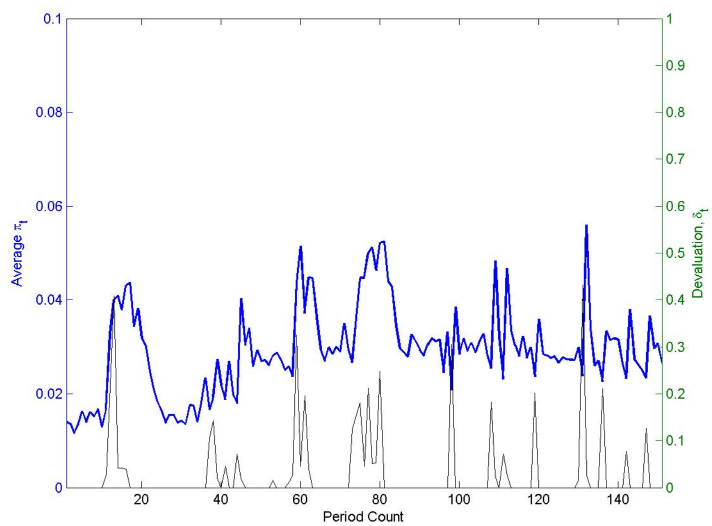

Figure 2: Extended Simulation - 12 agents, 5 rules per agent, probability of mutation 0.0825

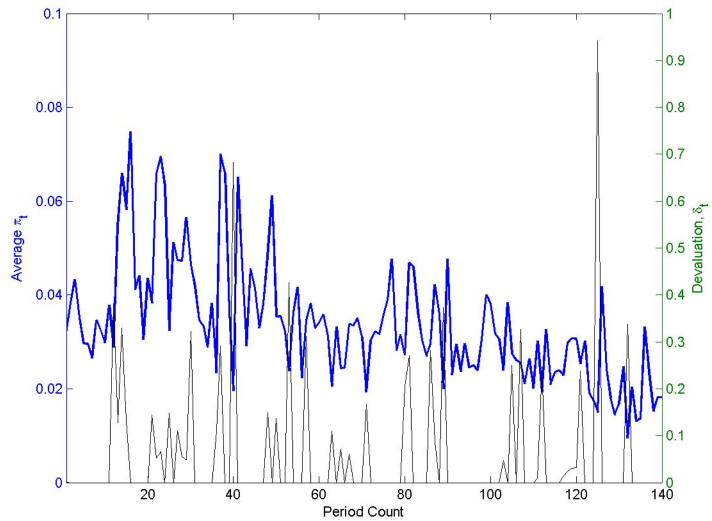

Figure 3: Treatment - 11 subjects

Simulation No.	Population	Rules	p_m	b	Std.Deviation	Skewness	Kurtosis	Jarque-Bera	AC(1) Coef.	Confidence Int.	
1	100	1	0.33	–	0.0699	1.0438	8.5243	32037.3309	-0.3265	-0.345	-0.3079
2	75	1	0.33	–	0.0753	1.0962	8.2406	30245.27	-0.393	-0.411	-0.375
3	50	1	0.33	–	0.0787	1.1404	7.904	28149.5239	-0.4139	-0.4317	-0.396
4	25	1	0.33	–	0.09	0.8078	6.8525	20615.9021	-0.4573	-0.4748	-0.4399
5	12	1	0.33	–	0.0982	0.5462	6.5964	18593.6343	-0.4945	-0.5115	-0.4775
6	100	1	0.165	–	0.0766	0.9016	12.9387	70990.1144	-0.5114	-0.5283	-0.4945
7	75	1	0.165	–	0.08	0.8307	13.2322	73981.4313	-0.5236	-0.5403	-0.5069
8	50	1	0.165	–	0.0797	0.8857	13.5166	77302.9049	-0.4883	-0.5054	-0.4712
9	25	1	0.165	–	0.0794	0.7467	13.8796	81062.1499	-0.478	-0.4952	-0.4608
10	12	1	0.165	–	0.077	0.4422	14.3286	85728.2631	-0.4991	-0.5161	-0.4821
11	100	1	0.0825	–	0.0798	0.3452	12.4875	65062.8705	-0.49	-0.5071	-0.4729
12	75	1	0.0825	–	0.0712	0.6327	17.3191	125442.2401	-0.4895	-0.5066	-0.4724
13	50	1	0.0825	–	0.0695	0.2827	17.2103	123345.5198	-0.5176	-0.5344	-0.5009
14	25	1	0.0825	–	0.0572	0.4267	28.7621	344448.0896	-0.4822	-0.4994	-0.465
15	12	1	0.0825	–	0.0658	0.1532	19.1618	152779.4133	-0.5041	-0.521	-0.4872
16	100	1	0.04	–	0.0638	0.0749	14.8354	91560.9185	-0.5026	-0.5196	-0.4857
17	75	1	0.04	–	0.0529	0.1593	19.4818	157927.693	-0.5048	-0.5217	-0.4879
18	50	1	0.04	–	0.0434	0.1856	34.4867	494835.243	-0.4865	-0.5036	-0.4693
19	25	1	0.04	–	0.0547	0.1293	30.0254	375070.3428	-0.4959	-0.5129	-0.4789
20	12	1	0.04	–	0.0829	0.1943	15.2031	96208.6146	-0.4899	-0.507	-0.4728
41	100	45	0.0825	–	0.0447	0.3807	24.4229	248376.0731	-0.5562	-0.5725	-0.5399
42	75	45	0.0825	–	0.054	0.4911	21.1627	186708.8063	-0.6947	-0.7088	-0.6806
43	50	45	0.0825	–	0.0552	0.5649	22.2541	206551.3147	-0.6779	-0.6923	-0.6635
44	25	45	0.0825	–	0.0597	0.3789	17.1078	121987.94	-0.7114	-0.7252	-0.6977
45	12	45	0.0825	–	0.056	0.4546	17.0052	120637.2949	-0.6358	-0.6509	-0.6206

Table 3: First Difference in Interest Rate Spread - Distribution Statistics

Simulation No.	Population	Rules	p_m	b	Std.Deviation	Skewness	Kurtosis	Jarque-Bera	AC(1) Coef.	Confidence Int.	
51	100	15	0.0825	–	0.0531	1.1422	13.1786	74415.9088	-0.5497	-0.566	-0.5333
52	75	15	0.0825	–	0.0551	0.8888	15.3142	98872.4335	-0.5256	-0.5423	-0.509
53	50	15	0.0825	–	0.0605	0.6319	11.8227	58806.3061	-0.568	-0.5842	-0.5519
54	25	15	0.0825	–	0.0622	0.5963	10.1505	43448.2459	-0.55	-0.5664	-0.5337
55	12	15	0.0825	–	0.0677	0.4301	9.902	41091.1048	-0.5885	-0.6044	-0.5727
56	100	5	0.0825	–	0.0464	0.5758	6.6146	18748.7372	-0.1635	-0.1829	-0.1442
57	75	5	0.0825	–	0.0521	0.6209	6.1288	16263.1434	-0.2912	-0.31	-0.2725
58	50	5	0.0825	–	0.0585	0.6048	5.4866	13127.9472	-0.3538	-0.3721	-0.3354
59	25	5	0.0825	–	0.0732	0.4029	5.2113	11563.8417	-0.4815	-0.4987	-0.4643
60	12	5	0.0825	–	0.0803	0.307	5.4475	12497.621	-0.5044	-0.5214	-0.4875
61	100	45	0.04	–	0.0534	0.8632	16.1728	110044.0002	-0.6442	-0.6592	-0.6292
62	75	45	0.04	–	0.052	0.5778	18.0145	135553.0267	-0.5669	-0.583	-0.5507
63	50	45	0.04	–	0.0553	0.5638	14.8698	92506.133	-0.6287	-0.644	-0.6135
64	25	45	0.04	–	0.0585	0.4676	14.7388	90727.2982	-0.6436	-0.6586	-0.6286
65	12	45	0.04	–	0.0605	0.5241	15.0211	94315.1026	-0.5907	-0.6066	-0.5749
71	100	15	0.04	–	0.0486	0.7894	9.6097	39448.3665	-0.319	-0.3376	-0.3005
72	75	15	0.04	–	0.0532	0.8449	9.0106	34958.8266	-0.3538	-0.3721	-0.3354
73	50	15	0.04	–	0.0628	0.5949	7.5715	24432.9029	-0.4578	-0.4753	-0.4404
74	25	15	0.04	–	0.0719	0.3839	7.4543	23355.7755	-0.5171	-0.5339	-0.5004
75	12	15	0.04	–	0.0735	0.4408	8.3718	29474.0369	-0.513	-0.5298	-0.4961

Table 4: First Difference in Interest Rate Spread - Distribution Statistics (Cont'd)

Simulation No.	Population	Rules	p_m	b	Std.Deviation	Skewness	Kurtosis	Jarque-Bera	AC(1) Coef.	Confidence Int.	
76	100	5	0.04	–	0.0538	0.2349	3.0786	4032.1203	-0.4344	-0.452	-0.4167
77	75	5	0.04	–	0.0637	0.233	2.2039	2109.0412	-0.508	-0.5249	-0.4911
78	50	5	0.04	–	0.0705	0.2113	1.8893	1557.5273	-0.5332	-0.5498	-0.5166
79	25	5	0.04	–	0.0787	0.2065	2.7314	3172.225	-0.5125	-0.5293	-0.4956
80	12	5	0.04	–	0.0846	0.17	3.8418	6184.8572	-0.5244	-0.5411	-0.5078
96	100	1	0.0825	1	0.0473	1.352	56.0627	1310620.723	-0.1491	-0.1685	-0.1297
97	75	1	0.0825	1	0.0527	1.6117	47.2117	931614.3243	-0.2821	-0.3009	-0.2633
98	50	1	0.0825	1	0.0569	0.9901	34.9589	510054.2031	-0.4244	-0.4422	-0.4067
99	25	1	0.0825	1	0.0367	0.0742	25.9926	281066.9713	-0.4975	-0.5145	-0.4805
100	12	1	0.0825	1	0.0242	0.4021	22.1091	203613.3823	-0.4771	-0.4942	-0.4599
116	100	15	0.0825	1	0.0434	0.5781	24.4355	248949.3194	-0.1512	-0.1706	-0.1318
117	75	15	0.0825	1	0.0464	0.7365	22.7333	215892.2112	-0.2455	-0.2645	-0.2265
118	50	15	0.0825	1	0.0514	1.0102	21.668	197011.1128	-0.2718	-0.2907	-0.253
119	25	15	0.0825	1	0.057	1.3648	20.4506	177082.8339	-0.299	-0.3177	-0.2803
120	12	15	0.0825	1	0.064	1.3874	19.2146	156789.7681	-0.3753	-0.3935	-0.3571
Treatment	15	–	–	–	0.065002	0.813709	10.7872	416.6527	-0.490306	(-0.0806)	[-6.08298]
Treatment	11	–	–	–	0.115439	0.330993	7.363626	104.7021	-0.823532	(-0.09155)	[-8.99530]
Treatment	11	–	–	–	0.140673	0.106237	5.862903	47.7312	-0.896168	(-0.08772)	[-10.2161]

Table 5: First Difference in Interest Rate Spread - Distribution Statistics (Cont'd)

Simulation No.	Population	Rules	p_m	b	Count(deval)	Ave.deval	Ave.non-deval
1	100	1	0.33	–	410	4.02	20.37
2	75	1	0.33	–	493	3.28	17.00
3	50	1	0.33	–	550	2.91	15.30
4	25	1	0.33	–	779	1.94	10.89
5	12	1	0.33	–	935	1.45	9.24
6	100	1	0.165	–	361	2.55	25.15
7	75	1	0.165	–	375	2.29	24.38
8	50	1	0.165	–	441	2.02	20.70
9	25	1	0.165	–	453	1.62	20.46
10	12	1	0.165	–	540	1.24	17.28
11	100	1	0.0825	–	464	1.24	20.31
12	75	1	0.0825	–	385	1.43	24.54
13	50	1	0.0825	–	427	1.11	22.31
14	25	1	0.0825	–	328	1.13	29.36
15	12	1	0.0825	–	503	1.13	18.75
16	100	1	0.04	–	526	1.02	17.98
17	75	1	0.04	–	516	1.01	18.37
18	50	1	0.04	–	338	1.03	28.55
19	25	1	0.04	–	391	1.08	24.49
20	12	1	0.04	–	621	1.15	14.95
41	100	45	0.0825	–	334	1.12	28.82
42	75	45	0.0825	–	460	1.24	20.50
43	50	45	0.0825	–	507	1.31	18.41
44	25	45	0.0825	–	583	1.19	15.96
45	12	45	0.0825	–	545	1.09	17.26
46	100	30	0.0825	–	417	1.48	22.50
47	75	30	0.0825	–	443	1.25	21.32
48	50	30	0.0825	–	481	1.38	19.41
49	25	30	0.0825	–	656	1.19	14.05
50	12	30	0.0825	–	605	1.14	15.41
51	100	15	0.0825	–	387	2.80	23.03
52	75	15	0.0825	–	404	2.07	22.68
53	50	15	0.0825	–	524	1.56	17.52
54	25	15	0.0825	–	664	1.32	13.74
55	12	15	0.0825	–	787	1.18	11.54

Table 6: Count and Duration Measures - Dynamically Relevant Devaluations

Simulation No.	Population	Rules	p_m	b	Count(deval)	Ave.deval	Ave.non-deval
56	100	5	0.0825	–	433	5.02	18.08
57	75	5	0.0825	–	532	3.93	14.86
58	50	5	0.0825	–	697	3.02	11.33
59	25	5	0.0825	–	1001	1.79	8.19
60	12	5	0.0825	–	1198	1.37	6.98
61	100	45	0.04	–	404	1.97	22.78
62	75	45	0.04	–	422	1.36	22.33
63	50	45	0.04	–	539	1.33	17.22
64	25	45	0.04	–	580	1.19	16.04
65	12	45	0.04	–	615	1.13	15.13
71	100	15	0.04	–	405	3.92	20.77
72	75	15	0.04	–	458	3.45	18.39
73	50	15	0.04	–	635	2.30	13.44
74	25	15	0.04	–	827	1.51	10.59
75	12	15	0.04	–	859	1.31	10.34
76	100	5	0.04	–	961	3.70	6.71
77	75	5	0.04	–	1360	2.57	4.78
78	50	5	0.04	–	1525	2.21	4.35
79	25	5	0.04	–	1547	1.80	4.66
80	12	5	0.04	–	1545	1.49	4.98
96	100	1	0.0825	1	92	3.76	104.92
97	75	1	0.0825	1	131	2.70	73.63
98	50	1	0.0825	1	228	1.39	42.46
99	25	1	0.0825	1	872	1.01	10.46
100	12	1	0.0825	1	2130	1.00	3.69
116	100	15	0.0825	1	165	4.54	56.40
117	75	15	0.0825	1	189	4.12	48.79
118	50	15	0.0825	1	243	3.18	37.97
119	25	15	0.0825	1	335	2.50	27.35
120	12	15	0.0825	1	450	1.90	20.32
Treatment	15	–	–	–		2.73	10.75
Treatment	11	–	–	–		1.27	4.64
Treatment	11	–	–	–		1.32	4.12

Table 7: Count and Duration Measures - Dynamically Relevant Devaluations (Cont'd)

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
$\overline{\pi_t} = \beta_1(L(1)\overline{\pi_t}) + \beta_2(D6) + \beta_3(D7) + \beta_4(D8) + \beta_5(D9) + \beta_6(D10)$										
0	–	–	–	–	β_1	β_2	β_3	β_4	β_5	β_6
					$\beta_1 + z\sigma_{\beta_1}$	$\beta_2 + z\sigma_{\beta_2}$	$\beta_3 + z\sigma_{\beta_3}$	$\beta_4 + z\sigma_{\beta_4}$	$\beta_5 + z\sigma_{\beta_5}$	$\beta_6 + z\sigma_{\beta_6}$
					$\beta_1 - z\sigma_{\beta_1}$	$\beta_2 - z\sigma_{\beta_2}$	$\beta_3 - z\sigma_{\beta_3}$	$\beta_4 - z\sigma_{\beta_4}$	$\beta_5 - z\sigma_{\beta_5}$	$\beta_6 - z\sigma_{\beta_6}$
					R-square					
1	100	1	0.33	–	0.3486	-0.0001	0.0023	0.0276	-0.0009	-0.0243
					0.3388	-0.0006	0.0019	0.0271	-0.0014	-0.0248
					0.3584	0.0003	0.0028	0.028	-0.0005	-0.0239
					0.7537					
2	75	1	0.33	–	0.3421	0.0002	0.0023	0.0254	-0.0014	-0.0228
					0.3311	-0.0003	0.0019	0.0249	-0.0019	-0.0233
					0.3531	0.0006	0.0028	0.0259	-0.0009	-0.0223
					0.6962					
3	50	1	0.33	–	0.2988	0.0006	0.0025	0.0232	-0.002	-0.0208
					0.2861	0.0001	0.002	0.0227	-0.0025	-0.0213
					0.3114	0.0012	0.0031	0.0237	-0.0014	-0.0202
					0.5987					
4	25	1	0.33	–	0.1633	0.0013	-0.0011	0.0198	-0.0018	-0.014
					0.1475	0.0007	-0.0017	0.0191	-0.0025	-0.0146
					0.1791	0.0019	-0.0006	0.0204	-0.0012	-0.0134
					0.4145					
5	12	1	0.33	–	-0.1057	0.0017	-0.0034	0.0135	0.0008	-0.007
					-0.1238	0.0011	-0.004	0.0126	-0.0001	-0.0077
					-0.0875	0.0024	-0.0027	0.0145	0.0018	-0.0063
					0.2529					

Table 8: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
6	100	1	0.165	–	0.4591	0.0005	0.0014	0.024	-0.0051	-0.0178
					0.4457	-0.0001	0.0008	0.0235	-0.0057	-0.0184
					0.4725	0.0011	0.0019	0.0246	-0.0045	-0.0172
					0.5687					
7	75	1	0.165	–	0.4205	0.0006	0.0005	0.0238	-0.0056	-0.0165
					0.4061	0	-0.0001	0.0232	-0.0062	-0.0171
					0.4348	0.0012	0.001	0.0245	-0.0049	-0.0159
					0.5194					
8	50	1	0.165	–	0.3473	0.0013	-0.0015	0.0204	-0.0053	-0.0126
					0.3314	0.0007	-0.0021	0.0197	-0.0059	-0.0132
					0.3632	0.0019	-0.001	0.021	-0.0046	-0.012
					0.4043					
9	25	1	0.165	–	0.095	0.0012	-0.003	0.0176	-0.0049	-0.0071
					0.0769	0.0006	-0.0036	0.0167	-0.0058	-0.0077
					0.1131	0.0019	-0.0023	0.0185	-0.0041	-0.0064
					0.2049					
10	12	1	0.165	–	-0.2596	0.0016	-0.0052	0.0104	-0.0022	-0.0009
					-0.2781	0.0009	-0.0059	0.0091	-0.0035	-0.0016
					-0.241	0.0023	-0.0045	0.0117	-0.0009	-0.0002
					0.1653					
11	100	1	0.0825	–	0.3552	0.0004	-0.0022	0.0166	-0.0098	-0.0044
					0.3379	0.0001	-0.0025	0.016	-0.0105	-0.0047
					0.3725	0.0007	-0.0019	0.0173	-0.0092	-0.0041
					0.3187					
12	75	1	0.0825	–	0.335	0.0009	-0.0021	0.0178	-0.01	-0.0058
					0.3181	0.0005	-0.0025	0.0171	-0.0107	-0.0062
					0.352	0.0014	-0.0017	0.0185	-0.0093	-0.0054
					0.3019					
13	50	1	0.0825	–	-0.0062	0.0005	-0.0031	0.0106	-0.0054	-0.0013
					-0.0257	0.0002	-0.0034	0.0097	-0.0063	-0.0017
					0.0132	0.0009	-0.0027	0.0116	-0.0044	-0.001
					0.1396					
14	25	1	0.0825	–	-0.2739	0.0003	-0.0037	0.0086	-0.0049	0
					-0.2926	-0.0002	-0.0041	0.0073	-0.0062	-0.0005
					-0.2553	0.0008	-0.0032	0.01	-0.0036	0.0005
					0.1351					
15	12	1	0.0825	–	-0.3447	0.0004	-0.0038	0.0035	0.0001	0.0007
					-0.3631	-0.0001	-0.0043	0.0023	-0.001	0.0002
					-0.3264	0.0009	-0.0033	0.0046	0.0012	0.0012
					0.1647					

Table 9: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations (Cont'd)

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
16	100	1	0.04	–	-0.1418	0	-0.0016	0.0021	-0.0002	0
					-0.161	-0.0002	-0.0018	0.0012	-0.0012	-0.0001
					-0.1225	0.0001	-0.0015	0.003	0.0007	0.0001
					0.1403					
17	75	1	0.04	–	-0.3487	0.0002	-0.0018	0.0027	-0.0014	0.0006
					-0.367	0	-0.002	0.0017	-0.0024	0.0005
					-0.3304	0.0003	-0.0017	0.0037	-0.0004	0.0008
					0.2303					
18	50	1	0.04	–	-0.2761	-0.0001	-0.002	0.0056	-0.004	0.0004
					-0.2948	-0.0003	-0.0023	0.0045	-0.005	0.0002
					-0.2574	0.0002	-0.0018	0.0066	-0.0029	0.0006
					0.133					
19	25	1	0.04	–	-0.2914	0.0003	-0.0022	0.002	-0.0003	0.0002
					-0.3102	0	-0.0025	0.0011	-0.0012	-0.0001
					-0.2727	0.0006	-0.0019	0.0029	0.0006	0.0005
					0.1234					
20	12	1	0.04	–	-0.1773	0.0002	-0.0027	0.003	-0.0001	0
					-0.1965	-0.0001	-0.0031	0.0023	-0.0009	-0.0004
					-0.1581	0.0006	-0.0024	0.0038	0.0007	0.0004
					0.0873					
41	100	45	0.0825	–	-0.0282	0.0013	-0.0025	0.0169	-0.0041	-0.01
					-0.044	0.001	-0.0028	0.0156	-0.0053	-0.0104
					-0.0125	0.0016	-0.0022	0.0181	-0.0028	-0.0097
					0.5738					
42	75	45	0.0825	–	0.2315	0.0014	-0.0024	0.0201	-0.0026	-0.0162
					0.2153	0.001	-0.0028	0.0191	-0.0036	-0.0167
					0.2476	0.0019	-0.0019	0.0211	-0.0016	-0.0157
					0.5489					
43	50	45	0.0825	–	0.2021	0.0016	-0.0025	0.0207	-0.0028	-0.0163
					0.1856	0.0011	-0.0029	0.0197	-0.0038	-0.0168
					0.2185	0.0021	-0.002	0.0217	-0.0018	-0.0158
					0.5162					
44	25	45	0.0825	–	-0.0286	0.0011	-0.003	0.0153	0.003	-0.0123
					-0.0463	0.0006	-0.0035	0.0141	0.0019	-0.013
					-0.0109	0.0017	-0.0024	0.0165	0.0042	-0.0117
					0.4626					
45	12	45	0.0825	–	-0.3512	0.0006	-0.0038	0.0068	0.0083	-0.0058
					-0.3684	0.0001	-0.0044	0.0052	0.0067	-0.0064
					-0.3339	0.0012	-0.0033	0.0084	0.0099	-0.0052
					0.4222					

Table 10: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations (Cont'd)

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
51	100	15	0.0825	–	0.5554	0.0002	-0.0016	0.0286	-0.002	-0.0248
					0.5457	-0.0002	-0.002	0.0281	-0.0025	-0.0253
					0.5652	0.0006	-0.0012	0.0291	-0.0016	-0.0244
					0.7867					
52	75	15	0.0825	–	0.4519	0.0013	-0.003	0.0264	-0.0036	-0.0224
					0.4405	0.0009	-0.0034	0.0258	-0.0042	-0.0228
					0.4634	0.0017	-0.0026	0.0269	-0.003	-0.022
					0.7299					
53	50	15	0.0825	–	0.3606	0.0011	-0.0029	0.025	-0.0037	-0.0196
					0.3476	0.0007	-0.0033	0.0243	-0.0043	-0.0201
					0.3737	0.0015	-0.0026	0.0256	-0.003	-0.0192
					0.6928					
54	25	15	0.0825	–	0.1171	0.0016	-0.0042	0.0222	-0.0022	-0.0151
					0.1017	0.0012	-0.0046	0.0213	-0.0031	-0.0156
					0.1325	0.002	-0.0038	0.023	-0.0014	-0.0146
					0.6015					
55	12	15	0.0825	–	-0.1283	0.0016	-0.005	0.0165	0.0022	-0.01
					-0.1452	0.0011	-0.0055	0.0153	0.0011	-0.0105
					-0.1113	0.0021	-0.0045	0.0176	0.0033	-0.0094
					0.5288					
56	100	5	0.0825	–	0.504	-0.0001	-0.0021	0.0201	0.0009	-0.0158
					0.4956	-0.0003	-0.0023	0.0199	0.0006	-0.0161
					0.5124	0.0001	-0.0018	0.0204	0.0011	-0.0156
					0.8278					
57	75	5	0.0825	–	0.473	-0.0005	-0.0022	0.0198	0.0006	-0.0156
					0.4638	-0.0008	-0.0024	0.0195	0.0003	-0.0159
					0.4823	-0.0003	-0.0019	0.02	0.0009	-0.0154
					0.8					
58	50	5	0.0825	–	0.3996	-0.0002	-0.0024	0.0186	0.0005	-0.0149
					0.3889	-0.0004	-0.0027	0.0183	0.0002	-0.0152
					0.4102	0.0001	-0.0021	0.0189	0.0008	-0.0146
					0.7558					
59	25	5	0.0825	–	0.1876	0	-0.0035	0.0169	0.0005	-0.0122
					0.1741	-0.0002	-0.0038	0.0165	0.0001	-0.0125
					0.2012	0.0003	-0.0033	0.0173	0.0009	-0.0118
					0.6888					
60	12	5	0.0825	–	-0.0671	-0.0001	-0.0049	0.0123	0.0029	-0.0072
					-0.0834	-0.0004	-0.0052	0.0118	0.0023	-0.0076
					-0.0507	0.0003	-0.0046	0.0129	0.0034	-0.0068
					0.5856					

Table 11: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations (Cont'd)

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
61	100	45	0.04	–	0.5592	0.0011	-0.0016	0.0266	-0.0044	-0.0226
					0.5481	0.0008	-0.002	0.026	-0.005	-0.023
					0.5702	0.0015	-0.0013	0.0271	-0.0038	-0.0222
					0.7513					
62	75	45	0.04	–	0.3356	0.0014	-0.0026	0.0215	-0.0056	-0.0142
					0.3206	0.0011	-0.0029	0.0207	-0.0064	-0.0146
					0.3505	0.0018	-0.0022	0.0223	-0.0048	-0.0138
					0.5874					
63	50	45	0.04	–	0.3152	0.0014	-0.0028	0.0213	-0.0047	-0.0148
					0.3	0.001	-0.0032	0.0205	-0.0055	-0.0153
					0.3303	0.0017	-0.0025	0.0221	-0.0039	-0.0144
					0.5811					
64	25	45	0.04	–	0.1147	0.0016	-0.0034	0.0181	-0.0012	-0.012
					0.0975	0.0011	-0.0038	0.0171	-0.0022	-0.0125
					0.1318	0.002	-0.003	0.0191	-0.0002	-0.0115
					0.5142					
65	12	45	0.04	–	-0.1427	0.0006	-0.0041	0.0134	0.0028	-0.0076
					-0.1606	0.0001	-0.0046	0.0121	0.0015	-0.0081
					-0.1247	0.0011	-0.0037	0.0146	0.0041	-0.007
					0.429					
71	100	15	0.04	–	0.5516	-0.0004	-0.0013	0.0232	-0.0001	-0.0195
					0.5431	-0.0006	-0.0016	0.0229	-0.0004	-0.0198
					0.5601	-0.0001	-0.001	0.0236	0.0002	-0.0192
					0.8267					
72	75	15	0.04	–	0.5302	0.0001	-0.0017	0.0228	-0.0001	-0.0196
					0.5214	-0.0002	-0.002	0.0225	-0.0004	-0.0199
					0.539	0.0004	-0.0014	0.0232	0.0002	-0.0193
					0.819					
73	50	15	0.04	–	0.4639	0.0003	-0.0022	0.0215	-0.0012	-0.0176
					0.4533	0	-0.0024	0.0211	-0.0016	-0.0179
					0.4745	0.0006	-0.0019	0.0219	-0.0009	-0.0173
					0.7725					
74	25	15	0.04	–	0.2378	0.0004	-0.0033	0.0185	-0.0012	-0.0127
					0.2234	0.0001	-0.0036	0.018	-0.0018	-0.0131
					0.2521	0.0007	-0.003	0.0191	-0.0007	-0.0123
					0.6537					
75	12	15	0.04	–	-0.0471	0.0003	-0.0049	0.0156	0.0001	-0.0079
					-0.0639	0	-0.0053	0.0148	-0.0007	-0.0083
					-0.0303	0.0007	-0.0046	0.0164	0.0008	-0.0074
					0.5316					

Table 12: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations (Cont'd)

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
76	100	5	0.04	–	0.4222	-0.0003	-0.0013	0.0093	0.001	-0.0081
					0.411	-0.0004	-0.0014	0.0091	0.0008	-0.0083
					0.4335	-0.0001	-0.0011	0.0094	0.0011	-0.008
					0.7464					
77	75	5	0.04	–	0.3334	-0.0003	-0.0016	0.0089	0.001	-0.0073
					0.3211	-0.0005	-0.0017	0.0087	0.0008	-0.0075
					0.3457	-0.0002	-0.0014	0.009	0.0012	-0.0072
					0.7383					
78	50	5	0.04	–	0.246	-0.0002	-0.002	0.0082	0.0016	-0.0071
					0.2324	-0.0003	-0.0021	0.008	0.0013	-0.0073
					0.2596	0	-0.0018	0.0084	0.0018	-0.0069
					0.7067					
79	25	5	0.04	–	0.0513	-0.0002	-0.0029	0.007	0.0025	-0.0052
					0.0352	-0.0004	-0.003	0.0068	0.0022	-0.0054
					0.0673	0	-0.0027	0.0073	0.0027	-0.005
					0.6015					
80	12	5	0.04	–	-0.1553	0.0001	-0.0042	0.0048	0.0043	-0.003
					-0.1727	-0.0002	-0.0044	0.0044	0.0039	-0.0033
					-0.1378	0.0003	-0.004	0.0051	0.0046	-0.0027
					0.5372					
96	100	1	0.0825	1	0.3745	0.0007	0.0002	0.0374	-0.0052	-0.034
					0.3627	-0.0001	-0.0006	0.0366	-0.006	-0.0347
					0.3862	0.0015	0.0009	0.0382	-0.0044	-0.0332
					0.6479					
97	75	1	0.0825	1	0.3173	0.0017	-0.0011	0.0291	-0.0064	-0.0232
					0.3026	0.0009	-0.0019	0.0282	-0.0073	-0.024
					0.3321	0.0025	-0.0003	0.03	-0.0055	-0.0224
					0.4567					
98	50	1	0.0825	1	0.0218	0.001	-0.0041	0.0149	-0.0043	-0.0064
					0.003	0.0004	-0.0047	0.0139	-0.0053	-0.007
					0.0406	0.0016	-0.0035	0.016	-0.0032	-0.0058
					0.1766					
99	25	1	0.0825	1	-0.48	0	-0.0046	-0.0018	0.0039	0.0026
					-0.4971	-0.0003	-0.0048	-0.0043	0.0013	0.0023
					-0.4628	0.0002	-0.0043	0.0008	0.0064	0.0028
					0.3534					
100	12	1	0.0825	1	-0.4539	0.0008	-0.0059	0.0022	-0.001	0.0031
					-0.4712	0.0006	-0.0061	-0.0046	-0.0078	0.0029
					-0.4365	0.001	-0.0057	0.009	0.0057	0.0033
					0.4291					

Table 13: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations (Cont'd)

No.	Pop.	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
116	100	15	0.0825	1	0.3808	0.0011	-0.0034	0.0376	-0.0031	-0.0318
					0.3717	0.0006	-0.0038	0.0371	-0.0036	-0.0323
					0.3899	0.0016	-0.0029	0.0381	-0.0025	-0.0313
					0.7984					
117	75	15	0.0825	1	0.3556	0.002	-0.0043	0.0371	-0.0027	-0.0325
					0.346	0.0014	-0.0048	0.0365	-0.0033	-0.033
					0.3652	0.0025	-0.0038	0.0377	-0.0022	-0.032
					0.7784					
118	50	15	0.0825	1	0.3079	0.0024	-0.0048	0.0368	-0.0031	-0.0307
					0.2972	0.0018	-0.0053	0.0362	-0.0037	-0.0312
					0.3186	0.0029	-0.0042	0.0375	-0.0024	-0.0301
					0.7414					
119	25	15	0.0825	1	0.1632	0.0014	-0.0046	0.0352	-0.0032	-0.026
					0.1503	0.0008	-0.0052	0.0344	-0.004	-0.0267
					0.1762	0.002	-0.004	0.036	-0.0024	-0.0254
					0.6374					
120	12	15	0.0825	1	-0.0145	0.0018	-0.0062	0.0327	-0.0033	-0.0202
					-0.0295	0.0011	-0.0068	0.0316	-0.0044	-0.021
					0.0006	0.0025	-0.0055	0.0338	-0.0023	-0.0194
					0.5432					

Table 14: Regression Analysis - First Difference in Average π - Dynamically Relevant Devaluations (Cont'd)

Population	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D1$	$D2$	$D3$	$D4$	$D5$
				$\overline{\pi_t} = \beta_1(L(1)\overline{\pi_t}) + \beta_2(D1) + \beta_3(D2) + \beta_4(D3) + \beta_5(D4) + \beta_6(D5)$					
–	–	–	–	β_1	β_2	β_3	β_4	β_5	β_6
				t_1	t_2	t_3	t_4	t_5	t_6
				R-square					
15	–	–	–	-0.118476	-0.004642	-0.000609	0.037645	-0.003965	-0.031612
				-3.113637	-2.188383	-0.287191	17.79897	-1.874918	-14.90833
				0.784863					
11	–	–	–	-0.325833	0.000645	0.005392	-0.004772	-0.001404	-0.005087
				-3.774778	0.236037	1.989777	-1.374776	-0.390415	-1.821604
				0.178759					
11	–	–	–	-0.216998	-0.002724	-0.00406	0.012254	0.000447	-0.007116
				-2.979921	-1.24158	-1.869841	4.386003	0.158368	-3.111756
				0.380659					

Population	Rules	p_m	b	$L(1)\overline{\pi_t}$	$D6$	$D7$	$D8$	$D9$	$D10$
				$\overline{\pi_t} = \beta_1(L(1)\overline{\pi_t}) + \beta_2(D6) + \beta_3(D7) + \beta_4(D8) + \beta_5(D9) + \beta_6(D10)$					
–	–	–	–	β_1	β_2	β_3	β_4	β_5	β_6
				t_1	t_2	t_3	t_4	t_5	t_6
				R-square					
15	–	–	–	-0.057469	-0.004096	0.007844	0.031718	0.000465	-0.025934
				-1.105364	-1.521912	2.822085	11.21665	0.164437	-9.737971
				0.606854					
11	–	–	–	-0.319874	0.001194	0.00262	-0.007453	0.002164	-0.004763
				-3.691546	0.413502	0.89769	-1.684557	0.479884	-1.626236
				0.16009					
11	–	–	–	-0.196566	-0.001454	-0.005393	0.011502	0.000851	-0.005358
				-2.509163	-0.667641	-2.51832	3.555103	0.26349	-2.325622
				0.363499					

Table 15: Regression Analysis - First Difference in Average π - Treatment Results