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An Agent-Based Model of Entrepreneurship

Matthew J. Holian
San Jose State University

Graham D. Newell
San Jose State University

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ABSTRACT

This paper presents an agent-based model of the Austrian market-process, adapted from Kirzner (1973) and Littlechild and Owen (1980), which explicitly incorporates entrepreneurship. The model is used to compare the effects of alertness and flexibility on the length of the equilibration process. We find that increases in alertness will not dramatically increase equilibration rates. The public policy implication of the model is that, if fast equilibration is desirable, then policy should focus on measures that increase flexibility rather than alertness. Two extensions to the baseline model are presented, including heterogeneous markets and traders.

Introduction

The intellectual environment at the University of Vienna during Joseph Schumpeter's time there as a student, spawned two subsequent strands of research. One is the strand which today carries his name—Schumpeterian, and for which the term evolutionary economics is also used. The second branch of research—Austrian, sometimes referred to as market-process economics—shares many similarities with the former, but differs sharply in other, especially methodological respects. The purpose of the present study is to explore the possibility of gains from trade. In particular we ask, what can be gained from exploring market-process ideas with an evolutionary approach?

Ours is not the first attempt at this problem. For example, Littlechild and Owen (1980) attempt to formalize Kirzner's (1973) theory of the market-process, which has recently received renewed attention from the burgeoning "entrepreneurial studies" literature (Shane, S.A. & Venkataraman, S.). Their mathematical model employs a Markov-structure and other features that are familiar to evolutionary modelers. However, mathematics in general is rarely employed in Austrian theorizing. In this regard, Littlechild and Owen (1980)'s model can be viewed as an attempt at integrating the two approaches.

However, although a common approach in evolutionary economics, to date, no one has conducted simulations of the Littlechild and Owen model. In other words, the integration exercise remains incomplete. This has meant that there are many properties of the model that remain unknown. Therefore our immediate aim is to run simulations, and to conduct several

"horse races" between the parameters of the model. The result is to shed new light on dynamic market processes, as well as to inform public policy, especially with regard to encouraging innovative activities.

Literature Review

Although we are not aware of any other formal (i.e. mathematical) attempts to integrate these two approaches, a number of scholars have in general considered how each can inform the other. For example, Richard Langlois and his co-authors (Langlois 1995, Robertson and Langlois, 2001) are explicit in drawing together Schumpeterian, evolutionary, Austrian and path-dependence insights in their theories of industrial organization. And Ulrich Witt (1995) has carefully discussed the methodological differences and similarities between the two approaches; indeed cataloging all the approaches at this task is beyond the scope of the present article. However, we believe our formal approach sheds new light on the nature of the market-process.

The remainder of this paper proceeds as follows. In the next section we describe the Littlechild and Owen model. Section three then describes our simulation approach; although largely reduced form, we did have to make some specific assumptions regarding aspects of the model that were not specified in the original exposition. Section four presents the simulation results; we also present a new visualization of the model here, which may encourage one to think about the issues in new ways. Finally, section five concludes by drawing public policy implications from our analysis.

The Littlechild and Owen (1980) Model

The model developed by Littlechild and Owen is an attempt to mathematically formalize the theory of the market process including two key features. (1) Knowledge is dispersed throughout society such that each person does not know the same things. And (2) over time people tend to discover new opportunities previously unknown to them; this is what Kirzner calls alertness and is the essence of his description of entrepreneurship. Therefore, entrepreneurship is what causes markets to tend toward an equilibrium price. In this section we will summarize the Littlechild and Owen model intuitively and define it mathematically, drawing directly from their 1980 paper.

Assume there is a homogeneous commodity that is bought and sold across a set of markets. For anyone buying or selling in these markets prices are taken as given but are determined by the preferences in each market represented by market demand curves. For simplicity the demand curves are constant over time and linear in price. Therefore, each market has a single price at a given time which is determined by the quantity of the commodity supplied to that market.

The good is traded between markets by a set of traders who buy only to resell. Each trader acts as an arbitrage agent buying in the low priced market and simultaneously selling in the high priced market. The amount that the trader transfers will be proportional to the price difference; however, the proportionality varies between traders by a constant and represents different degrees of flexibility. Traders do not necessarily know of all possible markets but only buy and sell in markets they are aware of. However, there is a potential for a trader to discover additional markets when the price in the unknown market is outside the range of prices in his known set of markets—either higher or lower.

The probability that a trader will discover an unknown market depends on two factors. One is proportional to the price difference of the unknown market to his known high and low priced markets. This means that an unknown market will have varying degrees of attractiveness to each trader depending on their existing knowledge. Second is the constant of proportionality unique to each trader that represents his innate alertness. This means that traders have a varying degree of ability to spot unknown markets with prices outside the range of their known markets—it is assumed to be constant over time.

Littlechild and Owen define their model mathematically on pages 364-367. Assume $M = \{1, 2, \dots, m\}$ is a set of markets and $N = \{1, 2, \dots, n\}$ a set of traders. Assume trader j knows of a subset of markets $M_j \subseteq M$, and can trade with any market i such that $i \in M_j$. Markets i and k are directly linked if any trader j knows both such that $i, k \in M_j$. Markets can be indirectly linked if they are not directly linked but there is a series of markets i_0, i_1, \dots, i_q , where $i_0 = i$ and $i_q = k$, so i_{l-1} and i_l are directly linked for $l = 1, 2, \dots, q$. Two markets are said to be linked if each pair of markets in the set is linked. Linked markets tend toward an equilibrium price through traders buying and selling instantaneously across known markets.

Thus, for $i, k \in M_j$, $y_{ik}^j(t)$ will be the quantity of the good at time t that trader j buys in market i and sells in market k . Therefore

$$(1) \quad y_{ki}^j(t) = -y_{ik}^j(t)$$

Let $x_k(t)$ be the net amount of the commodity supplied by all traders to market k at time t from all other markets, so that

$$(2) \quad x_k(t) = \sum_{\substack{j: \\ k \in M_j}} \sum_{i \in M_j} y_{ik}^j(t)$$

(Summation will be over M unless otherwise indicated)

From (1) it follows that the total net supply of all markets sums to zero

$$(3) \quad \sum_k x_k(t) = 0$$

Assuming that an equilibrium market-clearing price p_k results in market k , the demand curve for each market k can be represented as

$$(4) \quad p_k(t) = a_k - b_k x_k(t)$$

The weighted sum of prices $\sum_k (p_k(t)/b_k)$ is constant over time by using (3)

$$(5) \quad \sum_k \frac{p_k(t)}{b_k} = \sum_k \frac{a_k}{b_k} - \sum_k x_k(t) = \sum_k \frac{a_k}{b_k}$$

Therefore, the weighted average of market prices is also constant and is defined by

$$(6) \quad \bar{p} = \frac{\sum_k \frac{p_k(t)}{b_k}}{\sum_k \frac{1}{b_k}}$$

Consequentially, if a uniform price prevails across all markets, it must be \bar{p} . (Time subscripts for prices and quantities will be used for clarity and omitted elsewhere).

Each trader taking the price as given adjusts the amount which he transfers from one market to another at a rate directly proportional to the current prices spread between the two markets. Let

$$(7) \quad \dot{y}_{ik}^j(t) = \sigma_j (p_k - p_j)$$

if $i, k \in M_j$, and zero otherwise, where \dot{y} is the derivative with respect to time. The variable σ_j is the “flexibility constant and is assumed to be positive. A higher flexibility coefficient implies a stronger response to price differences. Substituting into (2)

$$(8) \quad \dot{x}_k(t) = \sum_{\substack{j: \\ k \in M_j}} \sum_{i \in M_j} \sigma_j (p_k - p_j)$$

This can also be written as

$$(9) \quad \dot{x}_k(t) = \sum_i \delta_{ik} (p_k - p_j)$$

Where δ_{ik} is defined by

$$(10) \quad \delta_{ik} = \sum_{\substack{j: \\ i, k \in M_j}} \sigma_j$$

δ_{ik} is the can be conceived as the strength of link between markets i and k , or the speed of response to price differences. For completeness

$$(11) \quad \dot{y}_{ki}^j(t) = -\dot{y}_{ik}^j(t)$$

$$(12) \quad \delta_{ki} = \delta_{ik}$$

and

$$(13) \quad \sum_k \dot{x}_k(t) = 0$$

Littlechild and Owen then prove their first of two theorems. The theorem is that for a set of linked markets the prices in those markets tend toward an equilibrium price. Markets that are not linked, however, do not generally trend toward a common price. Nevertheless, when the prices of unknown markets lie outside the range of prices known to any trader the unknown

markets have a certain amount of attractiveness to him. Introducing the possibility that traders can discover unknown markets will mean that the known markets M_j can change over time. Littlechild and Owen adopt a model of market discovery as a Markov process, so that the probabilities for each trader to discover a new market will depend both on the “attractiveness” of the unknown markets and his “entrepreneurial” ability.

Suppose trader j knows of the subset of markets $M_j(t)$ at time t , but does not know of market k so that $k \notin M_j(t)$. Additionally, $q'_j(t)$ is the lowest and $q''_j(t)$ the highest known price of trader j at time t . If $p_k < q'_j$ then buying in that market will offer an advantage to the trader; likewise, if $p_k > q''_j$ then selling in the market will offer an advantage to the trader, therefore when p_k lies outside the range of prices $[q'_j, q''_j]$ it will have positive attractiveness to the trader.

The attractiveness of market k for trader j at time t is

$$(14) \quad \rho_{kj}(t) = \max\{0, p_k - q''_j, q'_j - p_k\}$$

If market k is unknown to trader j at time t then the probability that he will discover it over a small time interval τ is approximately proportional to $\tau\rho_{kj}(t)$.

$$(15) \quad \lim_{\tau \rightarrow 0^+} \frac{\text{Prob}\{k \in M_j(t + \tau) / k \notin M_j(t)\}}{\tau} = \theta_j \rho_{kj}(t)$$

The constant θ_j , is positive and independent of time and markets. It can be thought of as the “alertness coefficient” of trader j . Traders with larger θ_j values are more likely to discover unknown markets that have a positive attractiveness.

This leads to the second theorem. Given theorem one—that linked markets will tend towards a common price \bar{p} —theorem two states that assuming conditional discovery of markets from (15), all prices tend toward a common price. Alternatively

$$\lim_{t \rightarrow \infty} p_k(t) = \bar{p} \quad \text{for all } k \in M$$

Our purpose is not to test the theorems directly; our focus will be on two parameters of interest, namely the flexibility coefficient σ , and the alertness coefficient θ . More specifically, we will operationalize the model through an agent-based computer simulation and compare the outcomes of the process while adjusting σ and θ .

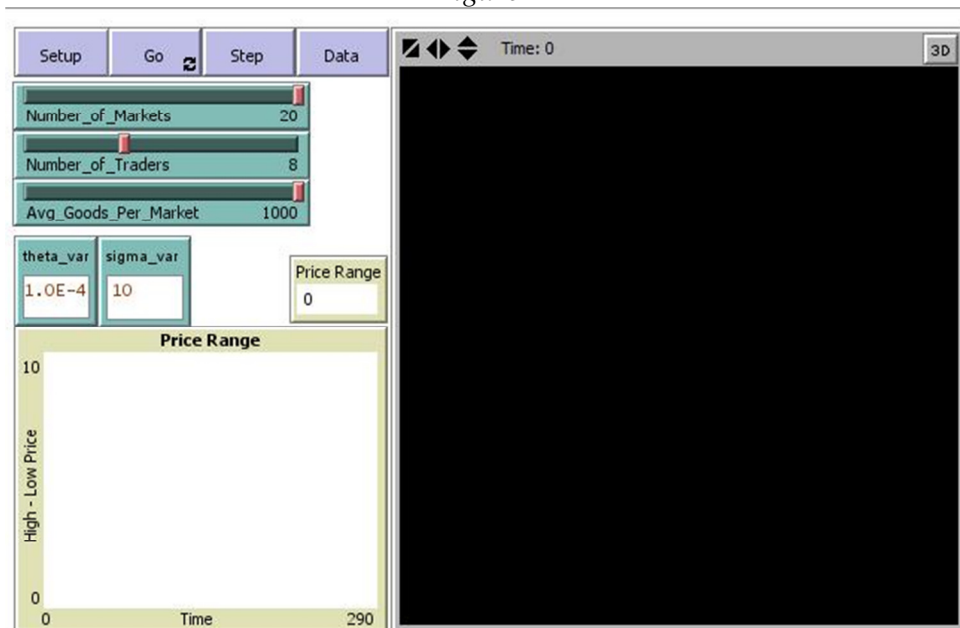
An Agent-Based Operationalization

Our model was developed using a multi-agent programmable modeling environment called NetLogo. Although mathematics and computer programming languages are very similar, challenges arise when attempting to adapt a mathematical model to computer languages due to subtle differences between the two. Therefore, the purpose of this section will be to describe the model we developed as an interactive computer program; and to develop a mathematical model from the program we created, highlighting areas of divergence from the Littlechild and Owen model.

Our model is an interactive visual computer program consisting of a graphical user interface which includes the *world*, four action buttons, five adjustable variables, and two feedback monitors (see Figure 1 below). The *world* is the visual space where the agents are represented and interact. The agents are: markets that appear as houses; traders that appear as people of varying colors. Links are non-agent objects connecting a trader and a market and symbolize trader awareness of a specific market. This space is also used to record the number of turns elapsed; turns are used to explicitly introduce a time component into the model and is labeled “Time”.

Five user-determined variables need to be defined prior to simulation. Three variables are controlled by *sliders* and include: the “Number_of_Markets” ranging from two to twenty by increments of one; “Number_of_Traders” whose values range from one to twenty also by increments of one; and “Avg_Goods_Per_Market” ranging from 100 to 1000 in increments of 100. The default values and ranges are arbitrary and can be edited to more suitable numbers as need be. In addition to the sliders two *input boxes* are used to set σ and θ mentioned previously. These boxes can input any real number; however, only positive values should be used. Values for each of these variables must be determined before running the simulation and any changes made during a simulation will not take effect until the model is reset.

Figure 1



Four buttons are available to the user to set-up/reset and run the model: ‘Setup’, ‘Step’, ‘Go’, and ‘Data’. The ‘Setup’ button is used after the variable values have been set and before any simulation is run. Clicking this button will run four procedures in the model. (1) The world will be complete cleared. (2) Markets will be created, the goods will be randomly distributed

among them, and prices will be determined. (3) Traders are created and assigned random links with two markets. And finally, (4) the global price spread—that is the highest price minus the lowest price—is calculated and reported. The simulation is setup and ready to be run.

Running the model requires use of the ‘Go’ or ‘Step’ buttons. The ‘Go’ button simply runs the ‘Step’ button continuously until ‘Go’ is clicked again or the global price spread reaches zero—all markets reach a common price. The ‘Step’ button is used to actually run the model and it has three procedures. First, traders exchange goods between known markets buying in low priced markets and selling in high priced markets. Not all available trades are made, but, the quantity of goods traded is limited by the trader’s σ -value and the difference in prices between markets. Second, after all traders have traded, a ‘tick’ is recorded to signify the completion of one round. Lastly, the graph is updated. The graph shows the price spread on the y-axis and ticks on the x-axis.

The ‘Data’ button is used to collect data on the number of turns required to reach global equilibrium prices. Clicking ‘Data’ will prompt the user to specify a file name and the number of simulations to run. Finally, the simulation will run the specified number of times and save a file as comma-delimited text.

Our model is intended to represent the mathematical model developed by Littlechild and Owen with particular discrepancies arising from the assumption required to adapt their model to an agent-based simulation. For our model the user determines the number of markets $M = \{1, 2, \dots, m\}$ where $2 \leq m \leq 20$, traders $N = \{1, 2, \dots, n\}$ where $1 \leq n \leq 20$, and an average quantity of homogeneous goods per market of $100 \leq 100 * y \leq 1000$ where $y = \{1, 2, \dots, 10\}$ and the total quantity of the goods available is $Y = 100 * my$.

The initial distribution of the goods is never explicitly addressed in the Littlechild and Owen model. However, for the purpose of simulation some initial distribution is required. Therefore, we assume that the goods are distributed to the markets through a series of rounds until all goods have been distributed. The order in which markets receive goods is random each round; Such that:

$$(i) \quad Y_m^i = 1 + \left\lfloor \mu \left[y - \sum_m \frac{Y_m}{N} \right] \right\rfloor, \quad \mu \sim U[0,1]$$

Where Y_m^i is the quantity of the good Y (rounded down to the nearest integer) distributed to market m during round i equal to one plus a random proportion μ of the average goods per market y less the average number of goods previously distributed to markets $\sum_m Y_m/N$. The total quantity of the good x initially distributed to market m will be

$$(ii) \quad x_m = \sum_i Y_m^i$$

Given the distribution of goods, we assume that a market-clearing equilibrium price results in each market, that the price p_k on market k is linearly dependent and determined by the net quantity of goods supplied to that market, and this relationship remains constant, so that

$$(iii) \quad p_k = a_k - b_x x_k$$

for simulation we assume $a_k = 2y, b_k = 1$

Traders act as arbitrage agents buying in a market with the lowest known price and instantaneously selling in the market with the highest price; however, we assume traders are initially only aware of two markets determined randomly. Each round consists of two stages with traders acting in random order in each stage. The first stage is involves exchanging goods

and the second stage involves potential discovery of unknown markets. For the exchange portion of a trader's turn each trader exchanges one good from the lowest priced known market to the highest priced known market. So that if trader j knows of a subset of markets $M_j \subseteq M$ the trader will exchange one good from market $k = \min\{p_k \in M_j\}$ to market $i = \max\{p_i \in M_j\}$. After the single good is transferred prices adjust and trader j will repeat this process σ_j times, reevaluating the lowest and highest known market prices. Traders have a constant σ value with larger σ values representing a relatively greater "flexibility" or willingness to trade a greater quantity of goods in each round.

The second task traders execute in a round is searching for new markets to trade with. Suppose the lowest known market price of trader j is p_k and highest known market price p_i from the subset M_j , further suppose there is an unknown market M_u , $M \supset M_u \notin M_j$ with a price $p_u < p_k$, or $p_u > p_i$, M_u will, therefore, represent a degree of attractiveness to trader j . Therefore, at time t trader j will have an "attractiveness" to market u of Rho, such that

$$(iv) \quad \rho_{uj}(t) = \max\{0, p_i - p_u, p_u - p_k\}$$

The probability that trader j will discover market M_u at time t is a function of $\rho_{uj}(t)$ and θ_j , more specifically the product of the two; where θ_j is an attribute of trader j representing the trader's "alertness coefficient". A larger θ value results in a greater probability that the agent will discover new markets. So we can say,

$$(v) \quad M_u \in M_j(t) \text{ iff } \theta_j \rho_{uj}(t) > \frac{1}{\mu} - 1, \quad \mu \sim U[0,1]$$

One of the results of this model of the market discovery process is that even if relative prices between different markets remain the same, nominal price differences will affect the probability that traders discover markets. For instance, if $p_i = 1$ and $p_u = 2$ then $\rho_{uj}(t) = 1$

and $P(M_u \in M_j(t)) = x$. The relative price of the unknown market u and known market i is 2:1. However, if the price level is doubled, ceteris paribus, then the probability that trader j will discover M_u doubles, such that $p_i = 2$ and $p_u = 4$ then $\rho_{uj}(t) = 2$ and $P(M_u \in M_j(t)) = 2x$. Finally, the rounds are repeated until all market prices are equal,

$$(vi) \quad \max\{p_m\} - \min\{p_m\} = 0$$

As an application of their model, Littlechild and Owen make some specific assumptions about the parameter values, to demonstrate one of their theorems. In particular, they assume $\sigma_1 = \sigma_2 = b_1 = b_2 = \theta_1 = 1$. Further assuming two traders, where trader 1 knows of two markets with different prices and trader 2 who knows of only one market, they proceed to demonstrate that the prices in each market will asymptotically approach equilibrium. Consequently, the unknown market will always represent a positive degree of attractiveness to trader 2 and yet, because prices are tending toward equilibrium rapidly, there is still a possibility that the market will go undiscovered by trader 2 even as $t \rightarrow \infty$. This is the result of the assumption that goods are infinitely divisible, however, in our simulation we assume that goods are indivisible. This change in assumption leads to a distinct difference in the outcome of our model, so that, $\lim_{t \rightarrow \infty} Prob(p_i(t) = \bar{p}) = 1$. However, even though our model reaches uniform pricing with certainty, just as with the Littlechild and Owen model it is possible for markets to go undiscovered by traders depending on the speed to which the markets equilibrate.

We will be interested in a knowledge-versus-equilibrium question in this section, but the focus will be on the speed of equilibration. A commonly used normative standard in the market-process literature is the speed of market equilibration (Harper, 2003, p. xx). Although markets may never attain equilibrium, as the environment “constantly throws up new ...” (Schumpeter,

Hayek or Kirzner quote here), it is perhaps possible to quantify differences in convergence rates. Indeed, by explicitly introducing time into the Littlechild and Owen model, we are able to conduct simulations and study the convergence rate, while varying certain parameters of the model. This will allow us to consider the real-world counterparts of these parameters, and thus to shed some light on public policy as it relates to entrepreneurship.¹

The objectives of this and the next section can be described as follows. First, we study the knowledge question; we consider the fraction of traders remaining ignorant, as in Littlechild and Owen, but we vary σ and θ , and study the resulting differences in ignorance levels. Second, we study the speed of equilibration in a simulation of the model; we will also look at how the convergence speed varies, while varying σ and θ . In addition, we allow for heterogeneous alertness, and also vary the alertness coefficient, unlike in Littlechild and Owen's example (367-369) where alertness was homogenous.

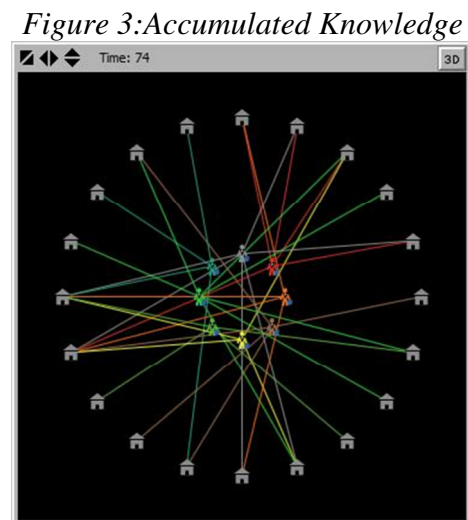
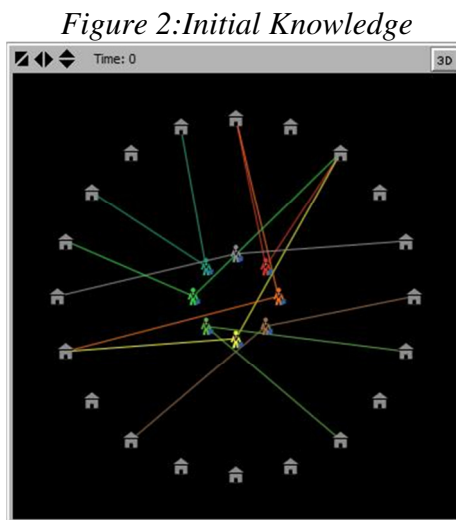
Simulations and Visualization

We present results in several forms. First, we present the summary statistics of the monte-carlo analysis. We also present graphs of the price difference rate, and the ignorance level over time. Finally, we present a visualization of the model, where traders and markets are aligned on two circles, and colored lines represent a link between markets. It turns out that this visualization allows for looking at the Littlechild and Owen model in a new way, and is able to produce some interesting images, especially of the complex role of alertness heterogeneity.

¹ We are the first to admit that the model is highly stylized and that policy makers should not base policy on the implication so of this model alone. Still, we highlight the policy implications of the model, for two reasons. One is that policy makers, like economists, rarely consider entrepreneurship at all, let alone the tradeoffs involved in policies that aim to encourage it. Therefore it is good for policy makers to consider the alertness-flexibility tradeoff, because it forces them to think about entrepreneurship in the first place. Second, even if they must be taken with

All simulations were carried out in the Netlogo programming environment, and the Monte Carlo simulations were verified in a spreadsheet. The Netlogo code is presented in the appendix, and computer files of all simulations reported herein are available upon request from the second author.

Figure 2 below shows the initial state of the world after setup. There are twenty markets and eight traders. Each of the traders has knowledge of two markets by default and this is represented by the colored links connecting traders and markets. Figure 3 shows how knowledge grows over time. In the particular simulation demonstrated in figure 3 the prices have reached equilibrium, and, although all markets are known by at least one trader, it is obvious that some traders have remained ignorant of some markets. In fact, no individual trader has knowledge of all the available markets.



Figures 4, 5, 6, and 7 below depict the price difference between low and high priced markets over time in three separate simulations with various values for θ and σ . Other variables

grains of salt, we consider policy implications to be the crucial output from any exercise in applied theory. Forcing theorists to consider policy implications is one way of dealing with Coelho and McClure's (2008) recent criticism.

remain constant: $m = 20$, $n = 8$, $y = 1000$, $b = 1$. For the baseline case

$\theta = 0.0001$ and $\sigma = 1$, while time to equilibrium is approximately 300 turns. Figure 5

represents a ten-fold increase in θ , so that, $\theta = 0.001$ and $\sigma = 1$, time to equilibrium is

reduced to approximately 260 turns. Figure 6 represents a ten-fold increase in σ , so that,

$\theta = 0.0001$ and $\sigma = 10$, time to equilibrium is approximately 50 turns. In the final case,

figure 7, we increase σ another ten-fold so that $\theta = 0.0001$ and $\sigma = 100$, time to

equilibrium is approximately 150.

Figure 4: $\theta = 0.0001$ and $\sigma = 1$



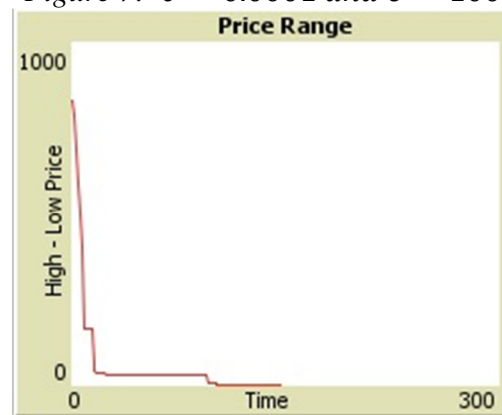
Figure 5: $\theta = 0.001$ and $\sigma = 1$



Figure 6: $\theta = 0.0001$ and $\sigma = 10$



Figure 7: $\theta = 0.0001$ and $\sigma = 100$



Our simulations show that the relative importance of σ and θ depends on the condition of the market. This is best demonstrated in figure 7, at the beginning of the simulation it is

observed that opportunities are very large and thus a high σ value leads to very quick adjustment. However, as those opportunities are diminished the relative importance of θ becomes apparent by the long periods without adjustment until the last opportunities are discovered and equilibrium is reached. The intuition is that where opportunities are very large little ability is required to identify and take advantage of them; on the other hand, where the opportunities are small a greater skill is required to identify and exploit those opportunities.

Policy Implications

In this section, we attempt to place the original model and our simulations in the context of contemporary entrepreneurship policy. While it is true that few researchers have followed up on the Littlechild and Owen model, we believe this is not due to the fact that model is inherently weak in this regard. Our opinion is that the insights from the model can only be realized in a simulation environment which we have presented here.

The simulations above discussed convergence and ignorance rates based on two variables: alertness and flexibility. It was found that increasing flexibility more often leads to faster convergence. What are the practical policy implications of this finding? We begin addressing this question by discussing public policies that have differential effects on alertness and flexibility.

Harper (2003) discusses several policies included in Table 1. This is obviously not an exhaustive list, but, for those policy we suggest, we are evaluating their impact on sigma or theta or both and if both than which is influenced more.

Table 1:

Policy	Affect alertness?	Affect flexibility?	Which does it affect more?
Favor market-oriented policies within a stable, rule-bound institutional framework that maximizes individual freedom and the scope for voluntary exchange			
Do not reduce rewards for successful entrepreneurship (by taxing pure profit) or increase the penalties for error and failure			
Rely on spontaneous ordering processes to address perceived problems with market outcomes			
If government action is thought to be necessary to address externalities, choose market-based regulation by rules over specific regulatory commands, taxes, or subsidies			
Remove government controls of inputs, outputs, wages, and prices			
Remove government-imposed barriers to new entry in all industries			
Abolish/Reduce Patent Rights			
Government intervention to control the use of monopoly power; and prohibit anticompetitive behavior			
Eliminate tariffs, import quotas, and restrictions on exports			
Remove international capital controls			
Remove direct regulation of exchange rates			
Establish a sound monetary framework (as the central monetary authority)			
Pursue price stability in the general price level			
Avoid using fiscal means for countercyclical policy tool to correct alleged market failures			
Reduce the level of government expenditure and maintain a balanced budget			
Broaden the tax base, and reduce and flatten tax rates			
Privatize state-owned enterprises			
Separate funding from provision of state health and educational services, and encourage private-sector crowd-in			
Tighten eligibility requirements and reduce levels of governmental social transfer payments.			

adapted from Harper 2003

Extensions to the Model

We will look at both heterogeneous markets (with an even initial distribution of goods, and with a random distribution of goods). We can also look at heterogeneous agents, especially who differ in alertness.

Conclusion

This paper has presented an agent-based model of the Austrian market-process, adapted from Kirzner (1973) and Littlechild and Owen (1980), which explicitly incorporates entrepreneurship. The model was used to compare the differential effects of alertness and flexibility on the length of the equilibration process. We find that increases in alertness will not dramatically increase equilibration rates. The public policy implication of the model is that, if society wants fast equilibration, then it should focus on measures that increase flexibility rather than alertness. Two extensions to the baseline model we presented which includes heterogeneous markets and traders.

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