Abstract
The relationship between equilibrium convergence to a uniform quality distribution and price is investigated in the Q-model, a self-organizing, evolutionary computational matching model of a fixed-price post-secondary higher education system created by Ortmann and Slobodyan (2006). The Q-model is replicated with price equaling its Ortmann and Slobodyan (2006) value $P^*$. Varying the fixed price between 0 and $2P^*$ reveals thresholds at which the Q-model reaches different market clustering configurations. Results indicate structural market robustness to prices less than $P^*$ and high sensitivity to prices greater than $P^*$.

Introduction (1)
Over the past two decades, the American post-secondary education system—the collection of colleges, universities, and institutes that offer education beyond high school—has expanded to accommodate growing student enrollment. From 1985 to 2005, full-time attendance at post-secondary institutions rose 33 percent (NCES 2007). Attendance rates were higher still for historically underprivileged groups. Nonetheless, the universally rising cost of a post-secondary degree in America threatens to erode the future socioeconomic gains of education. In the same twenty year period as above, average tuition, room, and board rose by 60 percent after adjustment for inflation, outpacing real household income and the availability of financial aid (NCES 2008). Furthermore, education grants are increasingly being displaced in favor of student loans (Baum et al. 2002). The latter trend raises the net cost of education, either pricing students out of pursuing a degree or creating debt. Thus, the relationship between price and access to education is explored here.

Uncovering the systemic causes and effects of rising tuition and student debt on actors in the education system will be vital in developing policies for sustainable market growth. Awareness of interrelated microeconomic and market structural effects of admissions strategies and pricing would likewise benefit an individual institution. Toward these related public and private ends, creating a simulated laboratory allows safe exploration of interdependency and uncertainty, system dynamics, and potential policies for improving market outcomes.

Building on the Q-Model
The following model and simulation experiments build upon the self-organizing economic models of Nicholas Vriend (1995) and Andreas Ortmann and Sergey Slobodyan (2006) in creating a decentralized market “culture-dish that allows [one] to explore how macro regularities emerge through the repeated local interactions of boundedly rational, heterogenous agents” (Ortmann and Slobodyan 2006). Vriend (1995) builds and explores the baseline dynamics of an evolutionary economy where homogenous firms and consumers seek transactions while behaving based on the success of past choices. Ortmann and Slobodyan (2006) generalize Vriend (1995) into the Q-model: a firm-consumer matching model that includes heterogenous agents stratified along a quality spectrum and is applied to the study of the post-secondary education system. Using the market analogy in the context of education, the terms firm, seller, school, institution, and university are used interchangeably. Likewise, consumer, buyer, and student are treated the same.

Agents in the Q-model prefer to transact with other agents in a similar quality range. Coupled with a Classifier System (CS) and Genetic Algorithm (GA) for weighting and creating behavioral rules, respectively, internal agent preferences give rise to an artificially learned equilibrium convergence to uniform market structure and stable aggregate behavior. Ortmann and Slobodyan’s (2006) results are also robust to scale.

However, price is fixed at $P = 1$ in Ortmann and Slobodyan (2006) and Vriend (1995), limiting either model’s power to simulate rising tuition and debt trends. Due in part to a firm’s quality being a weighted average of current attending consumer quality $Q_{\text{avg}}$ and its own profits $\pi$—a relationship exactly described later—changing a firm’s
price affects firm quality. Changing a firm’s quality shifts the range of consumers a firm prefers to seek. In a recent undergraduate thesis, Drutchas and Érdi (2009) replicate and modify the Q-model to include endogenous price-setting with initial average market price equal to its Ortmann and Slobodyan (2006) level \( P^* \). Average price converges to slightly less than \( P^* \) and aggregate values remain stable. Yet market structure, the distribution of firms across the quality spectrum, exhibits high instability and skewness regardless of profit weight calibrations of a firm’s quality update rule (Drutchas and Érdi 2009). Instability is undesirable from the standpoint of a system modeler because it limits replicability of results. High skewness of firm quality is undesirable in the market for education because it limits consumer access.

In an effort to move toward a model that has stability, extendability, and explanatory power, the effect of price on market structure in the Q-model is explored systematically. The replication of the Q-model and subsequent experimental results indicate the existence of asymmetric thresholds around \( P^* \) but beyond which market structure converges to different equilibria.

Model Structure (2)

Though some gaps in Ortmann and Slobodyan’s (2006) description of the Q-model are filled with facts from Vriend’s (1995) decentralized economic matching model, the underlying system structure of the Q-model is replicated here as closely as possible. Two types of boundedly rational agents—firms and consumers—interact by seeking transactions that satisfy internal agent preferences and making probabilistic stochastic choices.

All agents are initialized in the first period (semester) with a random quality \( Q \) from a uniform distribution to a quality spectrum \( M \), where \( Q \in M [0, 100] \). In every time period agents follow a multi-part economic protocol. Firms choose both how many units to produce and how many signals to send to eligible consumers about the units produced. In turn, consumers choose to apply to an eligible firm from among their received signals. Following evaluation of consumer applications, acceptance and attendance decisions are made.

Agents evaluate their success by income earned in the current time period. Each agent CS adjusts accordingly the likelihood of repeating their most recent decision if faced with a similar environment in the future. Consumer income \( I_C \) equals a boolean value representing consumer satisfaction: 1 if attending a firm, 0 if not. Firm income \( I_F \) equals the normalized value of profit \( \pi \) as a function of price \( P \), production \( Y \), demand \( D \), the number of signals \( S \), the marginal production cost \( C_Y \), and the marginal signaling cost \( C_S \), all scaled by \( Q_F \) (Ortmann and Slobodyan 2006).

\[
\pi = [P \cdot \min(Y, D) - C_Y \cdot Y - C_S \cdot S] \cdot \frac{Q_F}{100} \quad (1)
\]

\[
Q_{t+1} = \alpha_1 \cdot Q_{avg} + \alpha_2 \cdot \pi \quad (2)
\]

\[
I_F = (\pi / \pi_{avg}) \cdot U[0, 1] \quad (3)
\]

Unlike consumers in the Q-model, whose initialized quality is fixed throughout simulation, firms update their quality at the end of each period according to Equation 2 (Ortmann and Slobodyan 2006). Ortmann and Slobodyan (2006) calibrate the quality updating parameters \( \alpha_1 \) and \( \alpha_2 \) to fixed values that result in a symmetric steady state market structure uniformly distributed across the quality spectrum:

‘Symmetric steady state’ denotes situations where every firm shares the same number of agents, where every firm serves the same number of agents, where every firm has the same profit share . . . and where the quality of the firm equals the average quality of its consumers. We calibrate the model so that the average firm quality . . . equals the average consumer quality of 50 (which, given our assumption of uniform distribution of consumers along the quality spectrum \([0,100]\), is what we can expect on average).

Agent Signal Preferences

Both firms and consumers determine eligibility by checking an agent’s quality \( Q_{C,F} \) against their own internal preferences. Firms randomly choose with replacement a consumer and signal her only if her \( Q_{C} \) falls within that firm’s range of acceptable consumer quality \([Q_F - \Delta^C, Q_F + \Delta^C]\) (Ortmann and Slobodyan 2006). The lower bound is the firm’s own preference and allows firms to signal consumers who are of lesser quality but not beyond a low quality tolerance \([Q_F - \Delta^C]\). This reflects the tendency of universities to admit applicants of lesser quality because they at least generate revenue and at most benefit from education by a higher quality school. A uni-

### Table 3: Summary of Q-model parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run length</td>
<td>3000</td>
</tr>
<tr>
<td>Marginal Production Cost</td>
<td>( C_Y ) 0.25</td>
</tr>
<tr>
<td>Marginal Signaling Cost</td>
<td>( C_S ) 0.025</td>
</tr>
<tr>
<td>Fixed Price</td>
<td>( P^* ) 1</td>
</tr>
<tr>
<td>Maximum Acceptable Quality Gap</td>
<td>( \Delta^C ) 10</td>
</tr>
<tr>
<td>Firm Initial Rule Weight</td>
<td>( w_F ) 0.3</td>
</tr>
<tr>
<td>Consumer Initial Rule Weight</td>
<td>( w_C ) 0.5</td>
</tr>
<tr>
<td>Firm Stochastic Auction Error Term</td>
<td>( e ) ( N(0,0.075) )</td>
</tr>
<tr>
<td>Consumer Stochastic Auction Error Term</td>
<td>( e ) ( N(0,0.03) )</td>
</tr>
<tr>
<td>Firm Rule Updating Parameters</td>
<td>( b_1, b_2 ) 0.25, 0.4</td>
</tr>
<tr>
<td>Consumer Rule Updating Parameters</td>
<td>( b_3, b_4 ) 0.1, 0.1</td>
</tr>
<tr>
<td>Quality Updating Parameters</td>
<td>( a_1, a_2 ) 0.95, 0.1</td>
</tr>
<tr>
<td>Discard Probability</td>
<td>( \theta ) 0.025</td>
</tr>
<tr>
<td>GA Rate</td>
<td>( n ) 50</td>
</tr>
</tbody>
</table>
versity would not accept an applicant who would negatively affect university quality beyond the benefit of marginal revenue from that applicant’s attendance.

The upper bound is not a firm’s own preference but instead knowledge of consumers’ preference for only those firms with quality greater than \([Q_C - \Delta^F]\). In other words, a consumer will only accept a signal from a firm with \(Q_F\) greater than a minimum acceptance threshold. Consequently, the upper firm preference bound \([Q_F + \Delta^F]\) exists to avoid wasting a signal on an out-of-reach consumer who will only reject a firm’s signal because it is below their minimum acceptable quality. Even if, in theory, students accepted substandard signals, the upper firm preference bound makes sense in a real-world market where students with \(Q_C\) closer to \([Q_F + \Delta^F]\) are more likely to be signaled or pursued by higher quality schools that a student is more likely to attend in the absence of other differences between institutions. In contrast to a firm’s two-sided quality tolerance, consumers do not need to be symmetrically endowed in institutions. In contrast to a firm’s two-sided quality tolerance, consumers do not need to be symmetrically endowed in institutions.

Firms continue to signal eligible randomly chosen consumers until they run out of signals or eligible consumers. Afterward, the application process begins. A consumer is randomly chosen with replacement to make an application decision. Depending on the opportunities faced and the success of previous decisions, a consumer can choose to either apply to a firm from her list of eligible signaling firms (the KNOWN action) or to apply to the firm she attended in the last time step (the PATronizing action), if at all. If a consumer takes the KNOWN action, she randomly chooses with replacement to apply to each firm among eligible firm signals until she is accepted. With the PATR action, a consumer only applies to the firm attended in the last time step, if at all.

**Classifier System of Behavioral Rules**

In the Q-model, the agent mind is modeled by probabilistically calling on a stored set of weighted rules. Firms and consumers have differing sets of rules populating their respective Classifier Systems.

Firm behavioral rules consist of 20 encoded integer pairs representing the number of units produced and the number of signals allotted for sending to consumers. For mutation and generation of new rules by a GA, Vriend (1995) and Ortmann and Slobodyan (2006) encode the integer pairs in bitstrings of length 10, allowing integer values between 0 and 1023 \((2^{10} - 1 = 1023)\). Due to the absence of huge deviations in production from the average production level of 100, Ortmann and Slobodyan (2006) restrict production to \([0, 255]\) by setting the leftmost bits of an encoded production string to zero \((2^8 - 1 = 255)\), a convention continued here. Firm rules are initialized randomly by tossing a coin for every bit in a string to determine its value.

Consumer behavioral rules specify all of a consumer’s possible actions, but are not subject to a GA and do not change throughout the simulation. As in Ortmann and Slobodyan (2006):

\[\text{[Consumers’]} \text{ behavioral rules each have a conditional part and an action part . . . The conditional part determines if a rule will be activated . . . given the current state of the world while the action part encodes possible actions. Specifically, rules have the following form:}\]

\[
\begin{align*}
\text{IF} & \ (\text{SAT, no SAT, Indifferent}) \\
\text{AND} & \ (\text{INFO, no INFO, Indifferent}) \\
\text{THEN} & \ (\text{PATR, KNOWN})
\end{align*}
\]

Here SAT denotes a [consumer’s] satisfaction (being served last period), and INFO records whether a [consumer] has received this signal as an invitation to apply. Some rules use a coarser representation of the state of the world are indifferent to SAT, INFO, or both.

Consumers’ Classifier Systems are each populated by 18 permutations of the 3 possible SAT representations, 3 possible INFO representations, and 2 possible actions.

**Probabilistic Decisions.** The active rule determines each agent’s action and is picked in every time step by stochastic auction. Every rule that applies to the current environment faced by the agent submits a bid \(u\) that is a function of its rule weight \(w \in \mathcal{W}[0, 1]\), a rule updating parameter \(b_1\), and an error term \(\epsilon\).

\[
\begin{align*}
u &= wb_1 + \epsilon \\
w_i &= w_{i-1} \cdot (1 - b_1) \\
w_{i+1} &= w_i + b_1(1 - b_2) \cdot I \\
v_{i+1} &= v_i + b_2(w_i + b_2)
\end{align*}
\]

Each bid is disregarded with a discard probability \(\theta\). The highest-bidding remaining rule becomes active, pays an activation fee according to Equation 4, and the agent behaves according to the active rule. After the application process is complete and agent income \(I\) is evaluated, the active rule weight is updated as in Equation 5. The updated weight also updates the previously active rule as in Equation 6 to introduce a system of weight transfers where each weight acts as a weighted average of past income earned (Vriend 1995).

**Evolving Rules with a Genetic Algorithm.** Ortmann and Slobodyan (2006) endow the Q-model with a two-part evolutionary component: the Steepest-Ascent-Hill-Climbing algorithm and the GENITOR algorithm. After every period, firms make minor changes to their active rule. If demand does not equal production, both production and signaling are adjusted accordingly by 10% of the production-demand gap.
**FIGURE 1**: Market structure below the low-price threshold. Multiple clusters are maintained but skewness is heavily negative.

**FIGURE 2**: Market structure below the low-price threshold. 7 segments emerge with negative skewness.

**FIGURE 3**: Market structure at the low-price threshold. Modulo 6 market segments emerge and maintain stability.

**FIGURE 4**: Market structure near $P^*$. Modulo 6 market segments emerge.

**FIGURE 5**: Market structure at the high-price threshold. Attractors appear with frequent disruptions and slow convergence to 7 segments.

**FIGURE 6**: Market structure above the high-price threshold. Attractors appear with minimal market stability and high positive skewness.
Every $n$ time steps, or when there is a measured degree of convergence among existing rules, firm CS’s undergo the GENITOR algorithm to generate a new rule. Parent rules are randomly chosen from rules with weights in the 75th percentile and undergo a uniform crossover to create two children rules. Each bit of the children’s strings are subject to individual mutation, the rate of which depends on the convergence of existing rules in the 75th percentile. Vriend (1995) suggests that high convergence in the upper percentile should be accompanied by a mutation rate 0.1; low convergence should be accompanied by a mutation rate of 0.001. One of the two children is randomly chosen to replace another randomly chosen rule among rules outside the 50th percentile. The chosen children rule’s weight is initialized to the average weight of its parent rules. In the firm CS stochastic auction occurring after a new rule has been generated, the bidding error term $\epsilon$ is decreased.

**Experiments and Results (3)**

Characteristic results are presented below from the Q-model replication and experiments on fixed market price calibrations between 0% and 200% Ortmann and Slobodyan (2006) levels with a market of 12 firms and 1200 consumers. When price equals one as in Ortmann and Slobodyan (2006), aggregate firm behavior closely approximates the Q-model. Like in Ortmann and Slobodyan (2006) a firm’s success in the quality spectrum is largely dependent on initial position. Generally, quality spectrum convergence begins to appear around 500 iterations, a rate slightly slower than Ortmann and Slobodyan (2006), depending on the market scale. The replication results also display the characteristic segment disruptions and cascading behavior observed in Ortmann and Slobodyan (2006). This behavior is a result of a quality rising or falling firm moving into another market segment and displacing a competing firm from that segment.

Additional information is collected from the Q-model baseline with fixed price, attendance equals acceptance, and firms have an average of about 230 eligible students. In only a few time periods, all students are applicants in the model and satisfaction is above 90%, indicating good market coverage. Eligibility skewness is non-zero, but generally minimal in the Q-model baseline.

Varying price from [0, 2], four behaviors emerge, including the 6-segment equilibrium established by Ortmann. Heavily skewed quality distributions occur for prices lower than 0.5 (see Figure 1) or higher than 1.5 (see Figure 7). In the former case firms crowd the bottom of the quality spectrum; in the latter case firms crowd the top of the quality spectrum. Other aggregate values are stable but suboptimal for those configurations. Moving closer to 1 from both directions, simulation runs with price between 0.6 and 0.7 (see Figures 2 and 3) or 1.05 and 1.06 (see Figure 5) generally exhibit more disruptions and segment transmissions and form either 6 or 7 segments, often moving between the two. 6-segment equilibrium occurs in every run with price between 0.75 and 1.04 (see Figure 4). Occasionally, even in runs with price very near one, a high disruption market can emerge where no firm stays in a segment for over 500 periods, but comes to temporary rest or transitions again to another segment when an equilibrium segment has been reached. Prices above 1.06 create highly disruptive markets with no stability (see Figure 7). Yet, again, common equilibrium segments for other runs appear to be attractor points at which firms either rest for a time or change direction. Also, it should be noted that while prices below 1 bring market structure gradually to a different state, 1.06 is a hard upper threshold beyond which there is no market structural stability despite stable aggregates.

Though market structure is unstable in the Q-model when price is too far beyond a threshold above or below one, the aggregate behavior of firms and consumers in each model converges to equilibrium and in the absence of quality skewness greater than 1 or less than -1, are qualitatively similar. Also when price is scaled to [0,100], average firm quality converges on or near the scaled price.

The primary explanation for instability of certain price configurations is that firms receive either too little negative reinforcement in their CS in the case of high price and profits, or too little positive reinforcement in their CS when profits and price are low. One possible stabilizing solution would be to recalibrate the quality updating equation for different numbers of attractors and firm sizes. Additionally, modifying the Q-model to use a GA that does not encode integers as bit strings may lend itself to greater stability as random mutations of bits in a string can result in huge fluctuations.

**Discussion (4)**

Price investigation of the Q-model builds upon at least two distinct bodies of research, one coming from recent research on financial aid in American higher education and the other coming from the field of agent-based modeling.
Post-Secondary Higher Education Developments

A model that seeks to capture the salient features of an education system as a market for education service must take for granted at least some of the formal structural relationships shared by all educational institutions and all students. In an effort to gain deeper insight into real-world problems in the education market, the Q-model should be extended to represent the post-secondary education system more closely. Recent higher education trends offer some motivation for constructing a model that considers education finance.

Rising college-eligible students in the USA face an increasingly dire education finance system. Despite growing state and federal support for educational institutions, tuition prices have been rising in both the public and private sector faster than inflation, real household income, and the financial aid available to academically eligible students. The collective consequence of these trends is intuitive: families and individuals are less able to pay for education. An update to a report from the Congressional Advisory Committee on Student Financial Assistance estimated that in the next decade as many as 3.2 million eligible moderate and low-income students actively seeking a post-secondary degree will forego further education altogether due solely to an inability to pay (Goggin et al. 2006; Kelly 2008). Numerically, the above estimate is roughly equal to all of the 2007 high school graduates in the USA.

The implication of Baum’s (2002) finding that loans are increasingly replacing grants is that the traditionally accepted gains in lifetime income due to a post-secondary degree face erosion by long-term debt. If loans comprise too great a share of financial aid offerings, affordability of education is especially vulnerable in periods when banks and lending corporations are less willing to approve large loans. Furthermore, rising prices coupled with rising profit margins risk biasing the trade-off between relatively poor high quality students and relatively wealthy satisfactory students that require no aid in favor of the latter. Clearly, without an alternative source of aid or change in the current level and quality of financial assistance, the demographic makeup of higher education will tend to be less socioeconomically diverse. Without diversity, the education system cannot serve as a mechanism for upward social mobility—a key feature of the American education system since the mass scholarships allotted by the G.I. Bill after World War II.

There are a range of solutions with a commensurate range of credibility proposed for preserving wide access to higher education, including education savings plans, tax credits or deductions, increasing government education funding, and even penalizing institutions for overpricing tuition. Due to the externalities potentially caused by affecting change at either the institutional, governmental, or student level, however, policy-makers must carefully evaluate their approach lest they create deeper systemic problems. Thus, a risk-free simulation laboratory has clear benefits as an experimental and inferential tool for developing effective and sustainable methods to improve the current American educational finance system.

Agent-Based Economic Modeling

The model described above follows most closely the agent-based matching model framework of self-organizing economies assembled by Vriend (1995) and applied to education by Ortmann and Slobodyan (2006). Modeling emergent macro-behavior with GAs and an accompanying CS is a key feature of each model and continues a growing body of literature on the use of evolutionary programming in exploring complex and ill-defined social behavior. Ortmann and Slobodyan (2006), Vriend (1995), and numerous other evolutionary social models trace their lineage to the pioneering work of W. Brian Arthur (1991; 1994), especially his near-canonical El Farol bar problem.

In both works, Arthur argues that an economic model that begins to accurately approximate human behavior must account for local interactions of heterogeneous and boundedly rational agents. Economic agents should be heterogeneous because their experiences in the market will not be identical if interactions are decentralized and self-organized. They must also be considered boundedly rational because any significant level of complication prevents the formation of a well-defined problem, rendering logical deduction useless and requiring induction for any rationality to be preserved (Arthur, 1994). Ortmann and Slobodyan (2006) note the growing empirical support in psychology and economics for Arthur’s assertion that people are “intuitive statisticians” who judge the outcome of their decisions in the environment and inductively make subsequent decisions based on its predicted outcome (see Camerer, 2003; Cosmides and Tooby 1996; Gigerenzer, Todd, and the ABC Research Group 1999; and Cowan 2001).

Like its precedents, this version of the Q-model adopts bounded rationality and inductive reasoning as a fundamental assumption and mechanism, respectively, in modeling the locally interacting behavior of firms and consumers. Both agents possess a limited amount of market information and must probabilistically select their actions based on historical experience. Drawing from a list of rules for acting in their environment, the probability of calling any given rule changes through reinforcement learning. The greater past success (gaining education or profit) achieved by a rule, the more likely it will be called for use again.

It might be argued that the Q-model and previous models are not completely self-organized because a pre-existing matching protocol that bounds agent behavior is required in addition to agent preferences. Indeed, some level of initial order is necessary in simulation, regardless of one’s metaphysical perspectives on teleology or chaos. The Q-model and its precedents are structured so agents can determine decisions endogenously with no one agent directly influencing the decisions of another. Hence, the agents organize themselves instead of being directed by an external or centralized force.

Likewise, Vriend (1995) qualifies his matching model as
self-organizing at the methodological level because it follows neither a purely random process—an all but complete absence of organization—nor the deterministic, simultaneous, centralized, and perfectly optimal market auction as theorized by Léon Walras in the 19th century (see Morishima 1977). A simulation of the former type would resemble regression modeling, an approach defa to agent behavior. The latter approach, a Walrasian market model, has not only been analytically shown to be impossible in practice (Richter and Wong 1999), but it also fails to capture the axiomatic assumption of bounded rationality pervading current agent-based computational economic research (see Tesfatsion and Judd 2006).

There are numerous drawbacks to agent-based modeling (ABM), including the absence of globally optimal convergence (instead of local optimality, which occurs empirically and is analytically supportable), sensitivity of behavior to structural changes, arbitrariness of parameter settings, and the potential for producing simulation artifacts. ABM may produce results that have meaning only within the model’s boundaries. Nonetheless, ABM is uniquely suited for the study of emergent, self-organizing, and complex behavior in human systems. Recognizing both the advantages and disadvantages of ABM, Axelrod (1997) encourages researchers to re-engineer existing models and explain subsequent models as completely as possible to ensure replicability—a paramount concern in experimental science. Ortman and Slobodyan (2006) echo Axelrod’s (1997) call. For these reasons, experiments here, and in a previous paper (Drutchas and Érdi 2009), follow an established lineage of similar models with stable parameterizations and encourage future researchers to do the same. In this spirit, the replication of the Q-model will be freely available upon request as an applet, along with the Java source code and generalized implementation details in pseudo-code.

Conclusion (5)

Investigating fixed price in the Q-model reveals an asymmetric threshold enclosing $P^*$. Beyond these thresholds market structure deviates from the uniform modulo 6 clustering configuration found by Ortmann and Slobodyan (2006). Generally, if $P^*$ is multiplied by a value only slightly greater than 1 (~1.05), the quality spectrum destabilizes but displays brief attractions to a roughly uniform quality distribution. Conversely, $P^*$ can be multiplied by as little as 0.35 and remain stable in either a 6 or 7 cluster configuration. The implication is that lower prices will necessarily result in reduced aggregate profits but do not necessarily cause an unhealthy market. Higher prices, on the other hand, result in higher aggregate profits at the cost of the quality spectrum’s distributional uniformity. As a result, consumers in a lower quality spectrum consequently go unserved in a high price market.

There is some hope in the real-world education system. In 2008, the NCES reported that tuition increases have been in step with inflation. Unfortunately, any slowing growth in tuition prices may quickly be reversed by economic recession. Baum et al. (2002) report that the largest increases in tuition have come in times of recession. Additionally, greater government aid is either ineffective at lowering prices because tuition consistently increases beyond government funding, or because it acts as a subsidy that allows institutions to charge higher prices.

Whatever the case may be, continued expansion of ABM as a form of structural and relational exploration of complex human systems will in the long run favor stability through policy-making sensitive to the behavioral change resulting from a policy. The post-secondary education system is less likely to respond sustainably, even if temporarily stable, to measures that vilify or penalize actors (taxing students or universities). Instead, understanding interdependencies and dynamics will be integral in a long-term solution that aids American growth and innovation.

References


