An Agent-Based Simulation on the Market for Offenses

Pinata Winoto

Department of Computer Science
University of Saskatchewan
Saskatoon, Saskatchewan, SK S7N5A9, CANADA
piw410@mail.usask.ca

Abstract

The equilibrium of the market for offenses using agent-based simulation is studied. One of the potential applications of it is to seek optimal policy in governing an open multi-agent system, especially when heterogeneous agents may behave maliciously. A theoretical work by Fender (1999) is chosen as the basic framework for the simulation. The simulation results show more detailed properties of the market equilibrium compared to those taken from theoretical analysis.

Introduction

In the criminal studies, crimes can be grouped as economically driven crimes and non-economically driven crimes. Economically driven crimes (or *economic crime* for short) are primarily driven by financial gains and presumably follow the utilitarian concept; i.e., it is controlled by manipulating its pains (punishments) and gains (rewards). Generally, if there are victims left by a crime, it is called a predatory crime. In the human society, crime is a complex phenomenon. In the agent society, crime is less complex due to specific agent's intention/purpose, for instances, violating committed contract (committed by bidder agent), sending misleading information (committed by advertising agent), entering restricted area (committed by search agent), etc. The context of this paper is on the study of malicious agent society, which is characterized by economic and predatory crimes. However, the model used is based on the economic model of 'human' crime, which is still a controversial issue. For example, it is commonly assumed in the crime model that all criminals follow rational choice behavior. However, in the real world many criminals are addicted to alcohol/drugs. Yet, rational choice model may fit better in agents society, since all agents are pre-programmed to make rational decision to maximize their rewards. Therefore, One of the potential applications of this study is to seek optimal policy in governing open multi-agent systems, especially when heterogeneous agents may behave maliciously.

The preliminary study in this paper tries to verify and extend some theoretical foundations of the market for offenses. A recent work by Fender (1999) is chosen as the underlying theory in this study. Before entering the simulation design, the theoretical framework of crime from economists' perspective will be described in the next section.

The Economic Theory of Crime

The first study of crime, by means of modern economic analysis, is the seminal work by Gary Becker (Becker, 1968). Most of the current works by economists still follow genuine Beckerian, or mix it with other methods, such as game theory and information processing (e.g., Sah, 1991; Marjit and Shi, 1998). All of them aim to minimize the social cost of crime based on economic principles. Some basic theoretical frameworks in criminal studies are:

- **Micro-level:** The decision of a person to participate in an illegitimate activity (crime) depends on:
  1. *The expected gain from that illegitimate activity.* There are three major factors affecting the expected gain, i.e.,
     - Net return from an illegitimate activity, U_1, which equals to the return from the illegitimate activity minus its direct costs.
     - Perceived probability of conviction, p_c.
     - Net return if convicted, U_2, which equals to U_1 minus punishment.

     It is commonly assumed that an offender behaves as if to maximize his expected utility (e.g., Becker, 1968; Ehrlich, 1996; Sah, 1991; Fender, 1999). Formally, the combination of those factors could be represented by the von Neumann-Morgenstern Expected Utility:

     $$EU_{crime} = (1 - p_c)\, U_1 + p_c U_2$$

  2. *Certain gain(s) from legitimate activities, U_{legal}.*
  3. *Taste (or distaste) and preference for crimes, U_{taste}* --- "a combination of moral values, proclivity for violence, and preference for risk" (Ehrlich, 1996).

Generally, a person will commit crime if $EU_{crime} > U_{legal} + U_{taste}$. The right hand side constitutes the minimum value (threshold) for a person to enter the illegitimate market. If the value is big, then there might exist a group of people who never commit crime regardless of the penalty or conviction rate. For instance, assume that the crime is riskless (penalty = 0 or conviction rate = 0) and the highest EU_{crime} = Constant > U_{legal}. If there is a fraction of people whose $U_{taste} > EU_{crime} - U_{legal}$, then they will not commit crime regardless of how light the penalty or how low the conviction rate is. Therefore, given any value of EU_{crime} < riskless EU_{crime}, there is a fraction of people who will not commit crime when their $U_{taste} > EU_{crime} - U_{legal}$. The number of them will increase when EU_{crime} decreases.

- **Macro-level** (Ehrlich, 1996)**:** The market for offenses (crime market) is an abstract market where the demand and supply of crimes are met, where:
  1. The **Supply side** is determined by the distribution of "taste of crime", U_{taste}, or "legal income", U_{legal}, in the population. As described before, different "taste of crime" represents different thresholds for those people to commit crime. Therefore, higher expected return from crime causes higher participations in crime (the upward sloping of supply curve, see fig. 1).
  2. The **Demand side** is determined by the tolerance of crime, which is inversely related to the demand for self-protection, and the law enforcement. Higher self-protection causes lower expected return from crime, therefore reduces the crime rate. And a higher level of the law enforcement causes lower crime rates too (downward sloping of demand curve, see fig. 1).

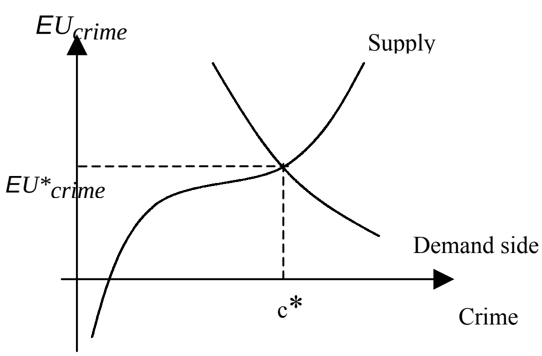

Figure 1. The market for offenses (Ehrlich, 1996)

- **Innovations made:** Many innovations of the classical economic model of crime have been made especially during the past decade. Among them are:
  1. ***Dynamic model:*** Many recent studies have begun to explore dynamic deterrence models, e.g. Davis (1988), Polinsky and Rubinfield (1991), and Leung (1995). The reason is that static models cannot accommodate many phenomena including recidivism, discount factor of future punishment, accumulation of criminal skills, etc. Some modifications of the classical model include:
     - Using multiple-period rather than one-period framework. In the one-period model, each person has only one opportunity to choose whether or not to commit crime. In the multiple-period model, each person has many opportunities to choose from. This model can accommodate the study of recidivism (Leung, 1995).
     - Adding the discount factor for future consumption and future punishment (Davis, 1988; Leung, 1995).
  2. ***Information process and social interactions:*** Sah (1991) added the Bayesian inference techniques into his model. The inference process is used to model how a potential offender predicts the probability of conviction from the information given by other people (cohorts, relatives, etc.). Under this model, Sah shows how different crime rates might occur under the same economic fundamentals. Generally, a potential offender is a social agent, equipped with the capabilities to recognize his environment, and therefore produces the dynamics of his society.
  3. ***Experimental Economics:*** Up to now, there is only one experiment reported on non-predatory crime, i.e. bribery (Abbink *et al*, 1999). Another equation-based simulation was conducted by İmrohoroğlu *et al* (1996).

While many literatures in economics have shown the existence of (theoretical) multiple equilibria in the crime market (e.g., Sah, 1991; İmrohoroğlu *et al*, 1996; Fender, 1999), little agent-based experiments have been done to study it. This paper study the existence of multiple equilibria based on model proposed by Fender (1999) by means of agent-based simulation.

Fender's Equilibrium Theory

Through mathematical derivations, Fender (1999) has shown that in the long run, there may exist multiple equilbria of the market for offenses (either stable or unstable equilibria). His model is solely based on Beckerian. The underlying intuition for the existence of the multiple equilbria is:

1. If the level of the law enforcement is constant and the crime rate is high and increases, then the conviction rate decreases (due to the diminishing marginal productivity of the investment in the law enforcement sector). Thus, an illegitimate activity becomes more attractive and the number of criminals increases.
2. If law enforcement is constant and crime rate is very low, then any marginal crime could be detected easily.

Based on those intuitions, Fender tries to show the existence of multiple equilibria in the crime market by means of mathematical analysis. This study is important for two reasons: if there are multiple equilibria, what criteria are needed to reach a preferred equilibrium? And, how to jump out from a not preferred equilibrium? The answer of the first question is mainly useful for the design of a new society. And the answer of the second question is useful for regulating an old society. In order to answer those two questions a model of the society and its crime market are needed. The basic assumptions in Fender's crime market are:

1. The economy consists of a population of n heterogeneous agents.
2. (n-m) agents never commit crime (honest citizens).
3. The remainder, m, are potential offenders, who can choose either to commit crime or to work legitimately, but not both.
4. Honest citizens always work and receive constant legitimate income w_h.
5. Potential offenders receive w_p from legitimate work (if they choose legitimate work); w_p is generated from a uniform distribution such that $w_p \in [w_h - \alpha, w_h + \alpha]$, where α is a constant value less than w_h.
6. If a potential offender commits crime and succeeds on it, his payoff is u_s.
7. But if he fails, he will be punished so that he will receive $u_f < u_s$. The probability of punishment p is equal for every criminal.
8. If the number of criminals is C, then the number of non-criminals (law-abiding agents/workers) is n-C, and the number of crime per non-criminal is $C/(n-C)$.
9. Only law-abiding agents are potential victims. If the average loss from crime is l, then the expected loss of each law-abiding agent is $lC/(n-C)$.
10. The government collects tax E from all law-abiding agents in order to pay the expenditure of the law enforcement; the tax (in \$) is equally collected from those agents no matter how much they earn from work; thus, every worker pays $E/(n-C)$
11. Every potential offender follows von Neumann – Morgenstern Expected Utility, so that he will commit crime *iff*

$$pu_2 + (1-p)u_1 - w_h + (lC+E)/(n-C) > 0 \qquad (1)$$

where p is the agent's perceived probability of punishment, which equals to the actual value of the punishment rate (perfect foresight).

From those assumptions Fender derives the relationships between p and C as follow:

1. There is a critical value w^* that satisfies $pu_2 + (1-p)u_1 - w^* + (lC+E)/(n-C) = 0$; which means that the agent, whose legitimate income equals to w^*, is indifferent between committing crime and working legitimately. Those agents whose $w_h > w^*$ would not commit crime, but those whose $w_h < w^*$ would.
2. Under the uniform distribution, the proportion of agents whose $w_h < w^*$ is $[w^* - w_h + \alpha]/2\alpha$.
3. Therefore, the number of criminals is $C = [w^* - w_h + \alpha]\, m/2\alpha$, or $w^* = w_h + \alpha + 2\alpha\, C/m$. By plugging this equation into (1), we get:

$$p = \left[\frac{1}{u_s - u_f}\right]\left[u_s - 2\alpha\frac{C}{m} - w_h + \alpha + \frac{lC+E}{n-C}\right] \qquad (2)$$

Equation (2) represents the relationships between punishment rate p and the number of criminals C (namely EC locus).

4. Another relationship between p and C (namely PP locus) can be derived from the relationship between the expenditure of the law enforcement and the probability of punishment:

$$p = \min\left[1, \frac{G(E)}{C}\right] \qquad (3)$$

Where a higher spending to fight crimes means a higher chance to catch criminals. Up to now, there is no consensus in the literature on what is the functional form to describe punishment rate (Pyle, 1983; İmrohoroğlu *et al*, 1996). Fender uses an increasing and concave function (diminishing marginal productivity of law enforcement) for $G(E)$.

Figure 2 shows the EC and PP locus for the following parameters: n = 2000, m = 1000, E = \$100000, u_s = \$2000, u_f = \$500, α = \$1000, w_h = \$2000, l = \$2000, and $G(E) = E^{0.4}$

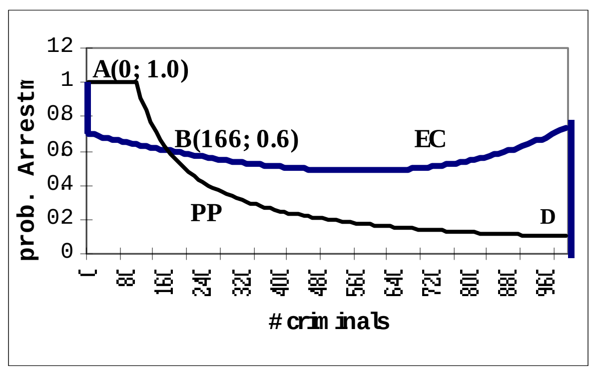

Figure 2. Theoretical multiple equilibria in EC and PP locus

Using equation (2) and (3), Fender shows the locus and equilibria. Basically, he believes that the stable equilbria (in fig. 2) are points A (0% crime) and D (100% crime). He believes that point B is an unstable equilibrium. The simulations in this paper will test his conjectures and then relax the assumption of perfect foresight, and finally show that the point-wise equilibrium may be violated under this relaxed assumption.

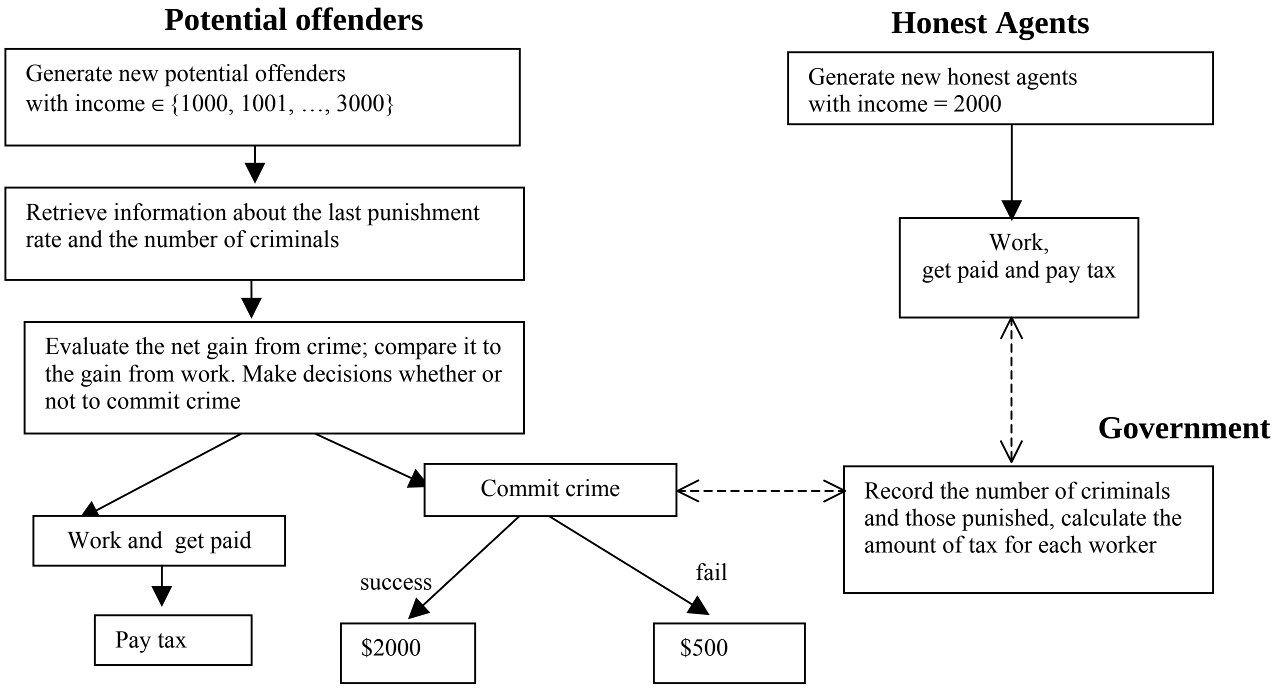

Figure 3. The process of the simulation with three type of agent: potential offender, honest citizen, and government

A Simulation of the Market for Offenses

General Model

Most of the assumptions used in this simulation are similar to those in Fender (1999). However, the following assumptions are added into the simulation:

A1. *The society follows a 10-generation overlapping model.*

In a *10*-generation overlapping model, all agents live for *10*-period of time. Generally, the overlapping generation model is introduced in the simulation for two purposes: maintaining the heterogeneity of agents by the born of new agents, and introducing social learning (inheritance of skills). This paper only concerns the former purpose and leaves the latter for future work.

A2. *The parameters used in the simulation are those shown in figure 2.*

All parameters in the simulation are hold constant, except that the potential offender's legitimate income is generated randomly.

A3. *The society runs for 100 periods only.*

A4. *Not all agents know exactly the past punishment rate.*

Most of the equilibrium theories assume that agents perfectly know all the information in the economy in the long run. However, most of the literatures in crime study do not support these assumptions: criminals use *perceived* probability of punishment rather than the true value, that perceived value may change due to new experience, and criminals actively try to reduce that probability (by gaining skills and experiences).

A5. *Each agent consumes his income, makes no saving.*

A6. *Criminals may be arrested during their action. No further hunting after that.*

Interactions

Figure 3 shows the interaction among three types of agents: potential offenders, honest citizens and the government. The simulation process follows the following algorithm:

Step1. Initialize the agents' wage; generate it randomly from uniform distribution.

Step2. For period = 1 to 100, repeat step3 until step4.

Step3. All potential offenders make decisions whether or not to commit crime. If a criminal succeeds, he will get some money from his victim ($2000). If he fails, he will be punished (receive $500).

Step4. The oldest generation dies and a new generation are born. Update the social parameters, e.g., crime rate, punishment rate, number of criminals, etc.

Each potential offender could only commit one crime during each period. In the next period, a new generation will be born and the old one dies, and the simulation continues. All agents are interacted to produce a time series data, e.g. crime rate, punishment rate, etc.

Experiments

The simulations are written in MS Visual Basic 6 and run on PC PentiumIII-600MHz. In this experiment, three treatments are conducted. The experiments are as follows:

T1. Benchmark
The benchmark experiment is based solely on the Fender's model, where all agents have perfect foresight. The result shows that the theoretical unstable equilibrium is attained when the initial punishment rate equals to 60.3%. From repeated trials, two possible outcomes are found: high crime rate equilibrium and low crime rate equilibrium (see fig. 4).

T2. Myopic agent in unstable equilibrium
Introducing myopic agents such that only *X%* of potential offender has perfect foresight, in which the initial punishment rate equals to 60.3% (unstable equilibrium). The value of *X* is chosen between 0 to 100. And those myopic agents generate their own perceived probability of punishment, which equals to a random value between 0% until 100% (high deviation) or between 50% until 70% (low deviation).

T3. Myopic agent in various initial probability of punishment
The fraction of myopic agents is set to 50%. Then, the effect of initial probability of punishment to the equilibrium is studied.

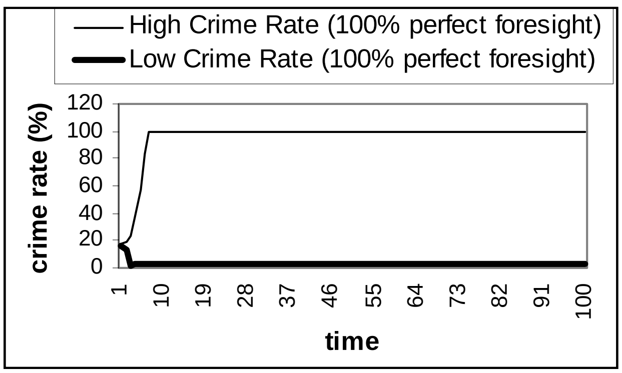

Figure 4. Theoretical multiple equilibria (high and low crime rate) are attained in the first experiment when the initial punishment rate equals to 60.3% (benchmark)

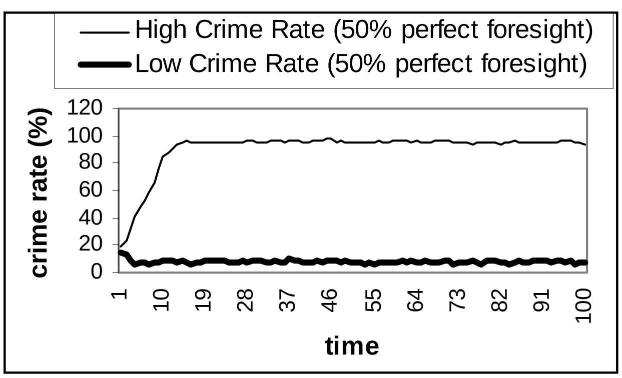

Figure 5. The effect of imperfect foresight to stable equilibria when the initial punishment rate equals to 60.3% (imperfection ratio = ±50%)

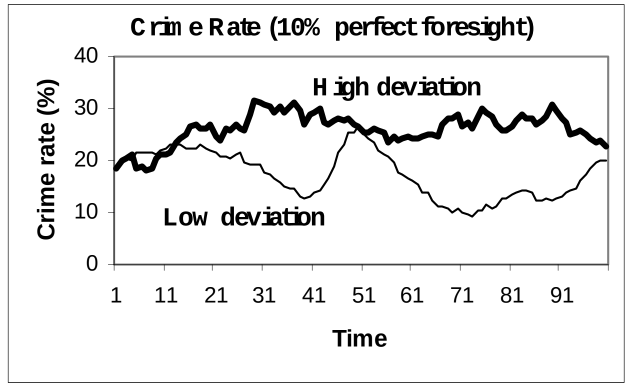

Figure 6. The effect of high imperfect foresight (only 10% population perfect foresight) to stable equilibrium when the initial punishment rate equals to 60.3%

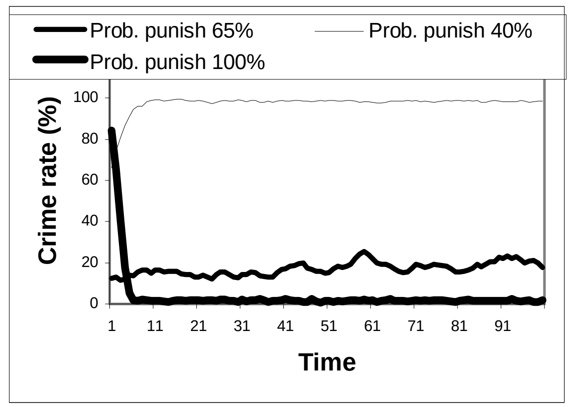

Figure 7. The effect of initial probability of punishment to the stable equilibria

Results and Discussions

Figure 5 until 7 show some of the experiment results. Figure 5 and 6 show the effect of myopic agents in the equilibrium. Basically, figure 5 is similar to figure 4 (benchmark). Some noises appear in figure 5 due to the imperfection of agents' judgement. Some agents may decide to commit/not commit crime even when the probability of punishment is very high/low. When the fraction of myopic agent increases, the noise becomes higher and affects the equilibrium. Figure 6 shows that the equilibrium (either high or low) is not attainable when the fraction of myopic agents increase to 90%. However, the effect comes not from the randomness of the perceived probability of punishment. Both high deviation (the random value of the probability of punishment is between 0% - 100%) and low deviation (the random value of the probability of punishment is between 50% - 60%) do not produce high or low equilibrium as what appears in figure 5. One possible explanation is that if agents rely on their perceived probability of punishment, then the true probability of punishment becomes less powerful in deterring crime and directing the society into either high/low crime rate equilibrium. However, it does not mean that the crime rate is not controllable at all. By changing initial punishment rate, the final equilibrium is still attainable (see fig. 7). It is shown in figure 7 that if initial punishment rate equals to 100%, the crime rate is forced to reduce until close to 0% (low crime rate equilibrium attained). And if initial punishment rate equals to 40%, the crime rate increases to almost 100% (high crime rate equilibrium attained). But if initial punishment equals to 65%, the crime rate moves between 11% to 26%, which seems to be stable.

Therefore, if the fraction of myopic agents is very high then the society only has a stable equilibrium. Up to now, no drift to bring the society into high/low crime rate equilibrium is found. Thus, the theoretical unstable equilibrium is not an unstable equilibrium in the presence of the imperfect foresight. And the stability of this equilibrium is maintained if the range of the initial punishment rate is between certain values. For instance, the values are 43% to 74% if the fraction of myopic agent is 90% and in low deviation case (not shown in the graph here). Thus, if the initial punishment rate is greater than 74% or less than 43%, then the equilibrium point will move close to 0% or 100% crime rate, respectively.

One main conclusion could be drawn from the results of the experiment: in the presence of imperfect foresight, a change of initial punishment rate will not cause the crime to automatically move to stable equilibrium. Only if we further raise/drop the punishment rate until certain value, the society moves to low/high rate stable equilibrium.

It is shown here that in principle, agent-based simulations can be used to study the crime market. Undoubtedly, there are many works left for future developments. For instance,

1. Finding optimal deterrence, e.g. using evolutionary computation techniques.
2. Extending the model into multiple types of crime.
3. Exploring various distributions of agents' properties, such as income inequality.
4. Introducing learning mechanism in gaining skills and experiences in crime.
5. Introducing self-protection of potential victims.
6. Adding more human-like characteristics of agents (cognitive) in decision-making, such as risk aversion.

Acknowledgements

This work is funded through a research assistantship from the Canadian Natural Sciences and Engineering Research Council. Partial of this work was done when the author was with Hong Kong University of Science and Technology and funded by postgraduate studentship. The author would like to thank Tiffany Y. Tang, Paul J. Brewer, and anonymous reviewer for their inputs and encouragement.

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