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The Interplay of Certainty, Severity, and Celerity in Punishment for Wrongdoing

Yushim Kim
School of Public Affairs
Arizona State University
411 N. Central Ave.
Phoenix, AZ 85004
Tel. (602) 496-1157
Email: ykim@asu.edu

Wei Zhong
School of Public Affairs
Arizona State University
411 N. Central Ave.
Phoenix, AZ 85004
Tel. (602) 496-1157
Email: wzhong1@asu.edu

and

Yongwan Chun
School of Economic, Political and Policy Sciences
The University of Texas at Dallas
800 West Campbell Rd.
Richardson, TX 75080
Tel: (972) 883-4719
Email: ywchun@utdallas.edu

ABSTRACT

While the deterrent effect of certainty and severity of punishment in addition to the interaction between the two has been evaluated for various criminal behaviors, few have assessed the influence of the celerity of punishment, or the additive influence of the interactions among those three factors. The objective of this paper is to gain insights on managerial decision-making to deter fraud using an alternative method that can simultaneously consider the three conditions. Using the case of vendor fraud in an Ohio health service delivery program, computer experiments generated three managerial decision hypotheses: First, to observe a reduction in fraudulent vendors, punishment with low certainty must be accompanied by high celerity. Second, severity becomes important in the long run when it is associated with low certainty and high celerity, but not with low certainty and low celerity. Finally, if punitive policy actions are taken on more than half of the fraudulent vendors identified in the system, the increase in certainty brings only a marginal effect. We discuss some policy insights to help a public agency design punitive actions given their goals and resources.

Keywords: Public Service Delivery, Fraud, Crime Opportunity, Deterrence Hypothesis, Agent-based Modeling

INTRODUCTION

Public service delivery systems are rarely, if ever, flawless in their design and implementation. In such complex delivery systems, unanticipated flaws such as a failure to monitor illegal behavior (i.e. fraud) can have serious adverse consequences for the system and ultimately damage the integrity of the public program. The public service delivery program consists of interdependent but goal-incongruent players who work together to pursue overlapping, but somewhat different goals. For example, public agencies frequently attempt to efficiently deliver public services to recipients by contracting with private service providers (vendors). While these vendors are responsible for delivering the services on behalf of the public agencies, they also attempt to maximize the profit they gain from the delivery. Program recipients are expected to improve their physical-economic conditions by complying with the program policies and consuming the services. However, such compliance occurs based on each player's priority, judgment, and environment. Public services are designed and delivered through routine procedures. In reality, however, the procedures are not necessarily implemented as intended. Unintended issues such as fraud occur, while goal-incongruent entities dynamically interacting and loosely interrelated with one another have specialized access to the system and behave opportunistically in order to take advantage of the system.

Fraud as 'a misrepresentation of asset values' (Sutherland, 1940, p.3) is a well-known problem in public programs (Ziegenfuss, 1996). For example, fraud, waste, and abuse are serious issues in the Unemployment Insurance Program (Heddell, 2002), the workers' compensation system is vulnerable to fraud (Wait, 1997), and fraud also appears in home health care programs (Vandenburgh, 2005). Among popular examples, agencies have reported that approximately 3 to 10 percent of U.S. health care spending is attributable to fraud (Altshuler, Creekpaum, and Fang, 2008; National Health Care Anti-fraud Association, 2007). In Fiscal Year 2007, 839 indictments and 635 convictions of health care fraud criminals were filed by the FBI (2007). Fraud in public service delivery programs can be committed by any member of the program, including recipients, vendors, and public employees. Among them, fraud committed by vendors has gained more attention due to increasing programs' expenditure and the social consequences. In the food stamp program, for example, trafficking – the exchange of public service benefits for cash – diverted about $395 million out of $18 billion per year between 1999 and 2002 (Macaluso, 2003). An early study on the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) program estimated that 22 percent of vendors might overcharge, and a follow-up study found that about 8 percent of all vendors actually overcharged (Oliveira et al., 2002). How to effectively set up sanctions to deter vendor fraud in such programs is an imminent policy question, especially in times of severe budgetary pressure.

In this paper, we explore insights decision-makers can gain regarding intervention strategies to deter vendor fraud in public service delivery programs using a dynamic simulation model that can mediate some of the shortcomings in the traditional methodological approaches. We first review the literature providing traditional and alternative frameworks to study illegal behavior in public service delivery programs. To integrate these frameworks, we discuss agent-based modeling and its implementation in the context of an Ohio public service delivery program. This model is then used to test various set conditions of punishment in order to examine the interplay of the severity, certainty, and celerity of punishment for wrongdoing. Managerial decision hypotheses were generated to inform theory and practice. We conclude this paper with a discussion on the role of this developing modeling approach in designing effective interventions to deter fraud in public service delivery programs.

CONCEPTUAL BACKGROUND

Crime Opportunity

A group of environmental criminologists has focused on crime as an event or action, and studies rooted in routine activity theory are interested in the spatio-temporal dynamics of crime (Cohen and Felson, 1979; Felson, 1994). In a fundamental way, routine activity theory is a micro-level theory where an individual is the unit of analysis (Eck, 1995). A main thrust of this theory is that crime depends upon opportunities presented by the routine activities of everyday life, where motivated offenders and suitable targets without guardianship are converged in time and space (Eck, 1995; Felson, 1994). These recurrent and prevalent interactions deliver crime opportunities to the offender (Cohen and Felson, 1979; Felson, 1987).

A divergent perspective of routine activity theory has emphasized a shift in the focus of crime research from the motivation or attribute of criminals to the context in which crime occurs (Groff, 2007). This idea has been enhanced by the recent development of the complex systems approach for crime settings. Complex systems are generally defined as dynamic systems that exhibit recognizable patterns of organization among system elements across spatial and temporal scales (Holland and Miller, 1991; Parker et al., 2003). The system elements are defined as situated within an environment that consists of other elements and are depicted as being adaptive, autonomous, and purposeful (Ashby, 1952; Franklin and Graesser, 1997; Schelling, 1978). Macro patterns emerge from complex interactions and interdependencies among these actors at the micro levels. By creating the phenomenon of interest from the interaction of heterogeneous agents and action rules, one can develop an understanding of how the phenomenon came about (Epstein and Axtell, 1996). Computer or computational modeling (i.e. agent-based models) has been used as a key instrument in gaining knowledge on complex systems (Epstein, 2006; Holland, 1998) and crime in particular (Bosse and Gerritsen, 2008; Brantingham and Brantingham, 2004; Eck and Lui, 2008; Groff, 2007; Kim and Xiao, 2008).

Another set of divergent perspectives can be found from the discussion on whether one should distinguish criminal offenders from targets regardless of crime type. The original routine activity theory was developed mainly to explain predatory offenses (Felson, 1987) and suggests that some are predisposes to greater risk as a target or greater motivation as an offender (Miethe and Meier, 1990). When this theory is extended to other types of offenses such as individual deviant behavior (Osgood et al., 1996) and white-collar crime (Felson, 2002), the sharp distinction between offender and victim is not applicable to a large share of illegal or deviant behavior (Herbert and Hyde, 1985; Osgood et al., 1996). To participate in illegal or deviant behavior, one needs to be present and willing when the opportunity arises. In everyday life, however, people behave dishonestly enough to profit but honestly enough to delude themselves of their own integrity (Ariely, 2007; Mazar, Amir, and Ariely, 2008).

Law Enforcement

In the traditional literature, much effort has been given to exploring the deterrent effect of law enforcement on crime. Since the publication of *Crime and Punishment* (Becker, 1968), the rational choice approach to crime has been rigorously studied and developed in various streams of literature (Cooter and Ulen, 2007). According to this perspective, the criminal is the analytic focus and is capable of making a rational choice. That is, an individual commits a crime only when he or she believes that the benefits from offending outweigh the potential costs. For a criminal, the expected cost might be produced by two elements: the certainty and severity of the punishment. An increase in the certainty or severity of punishment for an offense would increase potential offenders' perceived costs, discouraging individuals from engaging in criminal behaviors and lowering the crime levels in a society.

Most early empirical deterrence studies relying on aggregate data indicated a negative relationship between certainty of punishment and the crime rate, but a weak or non-existent relationship between severity of punishment and the crime rate (Antunes and Hunt, 1973; Ayres and Levitt, 1998; Levitt, 1998; Grogger, 1991; Tittle and Rowe, 1974). On the other hand, sociological studies based on the perceptual aspect of punishment explicitly attempt to assess the relationship between individuals' perceived certainty and severity of punishment and their behavior using cross-sectional surveys or panel data, and they have produced mixed empirical findings (Grosvenor, Toomey, and Wagenaar, 1999; Hollinger and Clark, 1983; Mendes, 2004; Piliavin et al., 1986).

While the deterrent effect of certainty and severity in addition to the interaction between the two has been evaluated for various criminal behaviors (Hollinger and Clark, 1983; Howe and Loftus, 1996), few have assessed the influence of the celerity of punishment (Ross, 1992), or particularly the additive influence of the interactions among those three factors (Grosvenor, Toomey, and Wagenaar, 1999). In addition, it is argued that to make punishment work, there is some critical but unknown level that punishment certainty should reach. Though certainty is an important deterrent factor, its influence cannot become operative before reaching that level in terms of changing individuals' behavior (Tittle and Rowe, 1974). Therefore, the conditions under which punishments are more or less effective needs to be reexamined by simultaneously considering the three relevant factors.

Paying attention to the mechanisms underlying the practice of fraud, particularly in public service delivery programs, where several entities are dynamically interrelated, we examined the conditions of punishment to refine managerial decision-making. Crime opportunity perspective helps us see fraud within a routine business mechanism of public service delivery programs. Rational choice perspective helps us examine the role of law enforcement in deterring fraud, but has limitations in providing insights on adaptive behavior within a dynamic environment (Gneezy and Rustichini, 2000; Paternoster, 1987). Therefore, each theoretical perspective provides compelling but partial views on fraudulent behavior in public service delivery programs and falls short of providing robust guidance. Combined, however, they provide a solid framework to model these complex aspects of fraud and to examine managerial decisions that effectively deter illegal behavior. In the following sections, we illustrate an approach to modeling fraud in a public service delivery program and present the computer experiments we conducted to gain new insights on a managerial decision-making.

METHODS

We examine fraud in a public service delivery program at the state level by modeling it as a complex system, using the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) in Ohio as a research context. An agent-based model of the program has been built to represent the system that presents fraud as an event. The model is then used to examine the interplay of the certainty, severity, and celerity of punishment in deterring fraud.

Ohio WIC

The WIC program aims to safeguard the health of low-income women, infants, and children up to age five who are at nutritional risk. The program provides nutritious supplemental foods, nutritional education, and referrals to health care and other social services. This program is available in all 50 states, the District of Columbia, 34 Indian Tribal Organizations, and the U.S. territories. There are 90 WIC state agencies administering the program through 2,200 local agencies and 9,000 clinic sites.[1] In Ohio, WIC currently serves approximately 300,000 participants each month with a budget of over $240 million per year. Ohio WIC has contracts with over 200 local clinics and 1,400 vendors, and the participants, local clinics, vendors, and state agency are the major players.[2] Since the operation of WIC is mainly at state and local levels, we do not consider the federal government in this research.

The Ohio WIC system can be depicted as shown in Figure 1 (a). The system consists of the *Ohio Department of Health*, which maintains the vendor management, certification, and payment management systems in support of the *local clinics* that certify *participant* eligibility. The participants, in turn, go to the *vendors* to redeem the benefit vouchers given to them by the local clinics. The vendors are paid by the state for the vouchers used at their stores. In building an ABM, the delivery of services and the behavior of the players can be modeled as a series of interdependent transactions among three agents. The local clinics and state agency can be collapsed into one agent. This agent issues vouchers to participants (a in Figure 1 (b)), monitors payments to vendors, and punishes vendors when they commit fraud (e). Participant agents redeem their vouchers at the vendors which are responsible for delivering food and nutritional supplements to participants on behalf of the public agency (b). Negotiation for illegal activities can occur during the benefit exchange between participant and vendor agents (c). Finally, vendor agents commit fraud by misrepresenting a value of a voucher used, if the voucher was collected during the fraudulent exchange (d).

<Insert Figure 1>

[1] http://www.fns.usda.gov/WIC/aboutwic/

[2] http://www.odh.ohio.gov/odhPrograms/ns/wicn/wic1.aspx

Agent-Based Modeling[3]

An analysis of systems that are subject to uncertainty (or modeling) is different from standard research methods in that the model itself is a subject of the research. Models are built based on assumptions until they reflect some known quality, quantity, or information of reality. While models are incomplete, some models can still be useful in exploring less well-known social processes such as fraud and other white collar crime. Standard research methods are good at identifying data patterns related to such a social process at single or multiple time points, but less effective in understanding the dynamic of hidden processes that led to the data pattern. Some computational models such as ABM have an intuitive appeal for social scientists because a social process can be modeled as individuals' adaptive decision-making behaviors. Once one develop a model that shows simulated patterns that reflect some known empirical patterns, the consequences of actions on the artificial system can be tested, informing decision-makers' intuition.

In this paper, we follow three steps for the current study: (Step 1) We built an ABM based on the business mechanism of Ohio WIC as the conceptual framework and some known information from the program as simulation inputs (i.e. the range of voucher values issued, actual usage of voucher values, and the distribution of store checkout lanes); (Step 2) Within the framework, we modeled illegal benefit exchange as an opportunistic behavior of risky agents, using a hypothetical attribute associated with individual decision-making (i.e. risk propensity toward fraudulent behavior). Decision outcomes of illegal benefit exchange with participants lead vendors to misrepresent voucher redemption amount to the public agency agent; (Step 3)

[3] The current simulation was designed using a Java language in conjunction with the MASON simulation toolkit from George Mason University (http://cs.gmu.edu/~eclab/projects/mason/).

When the public agency agent examines vendor agents' monthly sale activities and identifies a level of fraudulent vendors at an aggregate level, punishment scenarios are introduced. In the following, we explain details of step 2 to describe the modeling process and of step 3 for computer experiments.

Agents' Decision-making based on Attributes, Chances, and Rules

ABM consists of two components: agents with some attributes and action rules for individual decision-making. The key attribute of each participant and vendor in the model is "risk propensity" which is a hypothetical property used to model the distribution, chance, and change of an agent's propensity toward risky behavior. This propensity is randomly assigned at the initialization of the simulation in scale of 0 ~ 1, it influences agents' decision-making for illegal voucher exchanges (fraud involvement), and it is recursively influenced by their involvement in the illegal process. At the initial stage, participants' and vendors' risk propensities are assigned with a truncated Gaussian distribution with a mean of 0.40 and standard deviation of 0.40, ranging from min 0.00 to max 1.00. To our knowledge, there is no empirical evidence that shows the distribution of human risk propensity or how the propensity changes due to an illegal behavior. The assumption is that the higher the assigned risk propensity, the higher the probability of engaging in illegal behavior. Considering vendors as decision-making units, store size is also considered as a proxy of business type, represented by the number of checkout lanes of a vendor. Larger vendors are most likely to be national chains, while small vendors with one or two lanes are generally family-owned. Fraud occurs more frequently among small vendors relative to large vendors (GAO, 1999), so the smaller the vendor, the greater the probability of engaging in illegal behavior. Therefore, small vendors with high risk propensities have a greater chance of being involved in illegal exchanges. Table 1 presents heuristics to characterize the first fraud decision of participants and vendors based on these attributes and assumptions.

<Insert Table 1>

Two interaction rules were designed to guide agents' decisions. First, the participant faces a decision regarding the choice of vendors. Using the Huff spatial interaction model, participants' store choice was modeled (Store Choice Rule). In the Huff model (1964), the probability of a consumer visiting a particular store (P_{ij}) is calculated as a relative measure equal to the ratio of the utility of that store (U_{ij}) to the sum of utilities of all stores considered by the consumer. Formally, $P_{ij} = {U_{ij}} \big/ {\sum U_{ij}} = {S_i \cdot D_{ij}} \big/ {\sum S_i \cdot D_{ij}}$, where *i* and *j* indicate the consumer and store, respectively. The utility consists of two decision factors for store choice, store size of *i* (S_i), and distance between *i* and *j* (D_{ij}). During the initialization of the simulation model, each participant chooses a vendor based on the Huff's store choice model. In the original Huff model, store size is measured using store footage. In the current research, the number of checkout lanes was used as a proxy for store size. Euclidean distance was measured between the locations of participants and vendors. Using this rule, each participant would have a preference list for vendor selection. This model and its extensions have been validated in the marketing literature (Berman and Evans, 1995), and can also be justified by the fact that WIC participants are provided with store information such as store names, addresses, and telephone numbers within their administrative boundary upon enrollment.

The second rule is Fraud Negotiation Rule. When a participant visit a vendor based on the store choice rule, fraud opportunity is presented through the process of the benefit exchange. Depending upon the level of risk propensities, fraud negotiation between a participant and a vendor results in four possible decision outcomes: (1) both agents agree to involvement in illegal voucher exchange; (2) both agree not to be involved in illegal voucher exchange; (3) the vendor wants illegal voucher exchange while the participant does not; and (4) the vendor does not want illegal voucher exchange while the participant does want such exchange. If the outcome is agreed upon (the case of (1) or (2)), participant agents continue to visit the vendor and use their benefits in different manners (dishonest or honest) throughout the simulation unless random choice is introduced into the interaction process. For those participants who did not become involved in fraud and had a risk propensity greater than 0.6, a 1% of chance for random store choice was introduced to consider participants' movement to search for a fraud opportunity. If fraud negotiation fails (the case of (3) or (4)), a participant agent moves to the next vendor selected by the store choice rule and run the fraud negotiation rule again, until a successful exchange occurs. The fraud negotiation outcome and subsequent decisions regarding illegal benefit exchanges trigger the change of risk propensity for both participants and vendors. When a participant suggests an illegal benefit exchange to a vendor, the participant's risk propensity increases from the previous risk propensity by 10^{-4}. Rejection of the illegal exchange offered by a vendor leads the participant's risk propensity to decrease from the previous point by 10^{-4}. Vendors' risk propensities are also influenced by interactions with participants in fraud negotiation, using the same amount of positive or negative change. Thus, such a small change in numerous interactions leads some vendors to be involved in illegal behaviors more or less actively over time.

Two points need to be clarified: First, this research does not aim to make a claim on an individual's hypothetical attributes or rate of behavior change, but to design dynamic individual decision-making and behavioral outcomes attached to this decision and interaction rules. Second, ABM should be implemented to reasonably represent a system, in this case Ohio WIC. A well represented model can provide a baseline of vendor fraud informed from theory and practice. Here the baseline represents the level of fraudulent vendors without guardianship who actively engage in illegal behaviors to profit at the beginning, but relatively slowly increases over time due to existing policies and norms set.

Modeling Fraudulent Behavior as a Decision Outcome

Decisions during the fraud negotiation not only influence the change of risk propensity for one's next decisions but also manifest the outcome in the sales reporting behavior of vendor agents. In the current simulation, fraud is specifically defined as a misrepresentation of asset value by the vendor agent to the public agency agent when a voucher was collected from illegal benefit exchanges. In order to operationalize this behavior, the ABM is modeled with a series of probabilistic functions for each agent and interrelated processes regarding the use of vouchers at different times and multi-levels: (1) At every three steps (months), *the public agency agent* issue vouchers with a maximum face value that can be used at the vendor. Each voucher is randomly issued to participant agents with different face values. The average of the face values is $45 (e.g. consider a $40 voucher issued for a participant), (2) At each step, *participant agents* use a randomly decided voucher amount at the selected vendor. On average, participants use 75% of a maximum face value in vouchers (e.g. if it was randomly decided to use 75% of the voucher at the moment of exchange, the participant uses $30 of the $40 voucher), (3) For every exchange in each step, *vendor agents* record actual sales amount redeemed by a participant agent when a voucher is collected from a normal benefit exchange (e.g. $30). If a voucher is collected during an illegal voucher exchange, the vendor agent records the maximum face value instead of actual amounts used as if the participant agent redeemed 100% of the voucher (e.g. $40). Thus, an illegal exchange at an individual level occurs and vendor fraud is committed, and (4) Finally, *the public agency agent* monitors vendor agents' monthly sale activities because it is not practical to monitor every transaction due to the volume of information and the hidden process to the public agency agent. While not every participant visiting the vendor is involved in illegal exchange, the cumulated illegal voucher exchanges with greater portions of clients inflate the vendor's monthly sales amount compared to the true sales amount at the aggregate level. The public agency agent compares the sum of actual sales reported with the sum of maximum face values in vouchers collected from the vendor agent (a monthly redemption ratio) to identify an outlier. When the monthly redemption ratio at a specific vendor is greater than 90%, the vendor is considered a fraudulent vendor. These vendors become a potential set of vendors who will be punished according to a managerial decision-making.

Computer Experiments for Managerial Decision-making

Once agents' attributes and action rules help us determine whether certain explanations are plausible in leading the pattern observed or expected, we examine the consequence of possible actions within the system by modeling 'rules for change'. While public agencies continuously monitor vendors' monthly sale activities, they take punitive actions in response to fraudulent vendors in various ways. These policy actions combine set conditions of punishment such as certainty, severity, and celerity. Certainty is the probability of being punished (i.e. chance of being caught), severity is the harshness of punishment (e.g., the amount of the fine), and celerity is the swiftness of punishment (the time between when the criminal is caught and when the actual punishment is administered). In this simulation, certainty refers to the percent of fraudulent vendors that will be punished by a public agency agent (10%, 30%, 50%, 70%, and 90%). In regards to celerity, low, medium, or high imply interventions for fraudulent vendors caught after 2 years (24 steps), a year (12 steps), or 6 months (6 steps), respectively. In the current simulation, a step represents a month. Severity (low (0.1), medium (0.2), and high (0.3)) is more contextual, and may be interpreted as different types of sanctions (i.e. a warning letter, contract termination, or civil penalty). The range of severity values were designed given the scale of risk propensity (0 ~ 1). Severity values will be subtracted from the vendor's current risk propensity when a fraudulent vendor receives a punishment. After that, the vendors renegotiate with their clients based on adjusted risk propensities which also influence subsequent fraud decisions and behavioral choices. This behavioral change due to punishment leads vendors to less engage in illegal voucher exchanges which helps them be avoid of being identified as fraudulent during the next monitoring. Table 2 summarizes the description of model components and information type and source. Figure 2 summarizes the process of store choice, fraud negotiation, and punitive actions, as well as changes in risk propensities due to these rules.

<Insert Table 2>

<Insert Figure 2>

RESULTS

Model Verification

The verification and validation of social simulation models is challenging (Price, 2004). We attempt to verify the current simulation model by examining whether the model presents qualitative and quantitative descriptions of vendor fraud in the Ohio WIC program. To check whether the simulation generates consistent information with assumptions made, we examined a baseline level of fraudulent vendors in the system over time using vendors' sales information and a type of vendor that was identified as fraudulent. The simulation generated 200 vendors with 10,000 participants served by one public agency in each simulation. We ran the simulation 20 times.

There are two sources of information on the level of vendor fraud in the program. The level of fraudulent vendors from a sample county of Ohio WIC was identified by three different risk indicators in April 2004: 6.8% by a vendor redemption ratio, 9.6% by actual sales per checkout lane, and 8.5% by food costs per participant per vendor (Kim & Xiao, 2008). Early nation-wide WIC vendor studies also reported similar levels of fraud by service providers (overcharge): 22% in 1991 (estimation) and 8% in 1998 (actual investigation) (GAO, 1999; USDA, 2001). The limitations of this information are two-folds: First, there is a discrepancy on the known level of vendor fraud in the WIC program depending upon an examination approach (i.e. by criteria used for fraud identification or from confirmed cases vs. estimated levels). Second, the information presents fraud patterns as a snapshot at times of inspection. We do not know the trend of vendor fraud in the WIC program since its establishment. We only know the level of vendor fraud within a certain range at a certain time point. Thus what is possible is to present the baseline level of vendor fraud within the range mentioned above during the simulation.

In generating the fraud vendor baseline in the system, we also simplified the fraud identification method that the public agency used. In the current simulation, the fraud level is identified using a vendor's monthly redemption ratio criteria because two other risk indicators (monthly sales per checkout lane and food costs per participant) are simply different ways of identifying outliers using vendors' sale activities. At time 100, the simulation showed that an average vendor redemption ratio was 81%. Given the level of voucher usage designed, the ratio would be approximately 75%, if there was no fraud in the system. The 8.6% of vendors were identified as redeeming greater than 90% of the sum of maximum voucher values collected at the vendor. Without any intervention, the level of fraudulent vendors identified using this indicator slowly increased over time because some agents maintain their involvement in illegal voucher exchanges without tight monitoring. In addition, we checked the level of fraudulent vendors in the system by store size, in order to see whether the simulation output reflects the assumption correctly. Figure 3 presents the percent of fraudulent vendors identified in each group of store size at time 100, 200, and 500. Numbers in the parenthesis imply a total number of vendors with the number of checkout lanes. For example, there are 49 one lane vendors in the simulation. Approximately 18% of the vendors (9 vendors) were identified as fraudulent at time 100, 26% (13 vendors) at time 200, and 36% (18 vendors) in time 500. This figure shows that fraudulent vendors were mainly identified among one or two lane vendors and some larger vendors were identified as fraudulent later in the simulation.

<Insert Figure 3>

Deterrent Effects of Punishment

The public agency agent monitors vendor sale activities every six months (6 steps) after time 100 where the baseline reaches less than 10%. Once a set of fraudulent vendors is identified, the fraudulent vendors that will be punished are randomly selected given the level of certainty. Punitive actions accompanying severity values are implemented at different intervention intervals based on celerity. At the end of the simulation, the deterrent effect of punishments based on each set condition of certainty, severity, and celerity were examined to identify the conditions of punishment that performed most or least effectively in deterring fraud in the policy system. Using the simulation results, the average percent of fraudulent vendors was monitored at four different times (5, 10, 20, and 30 years after first intervention) and used for the evaluation of punishment scenarios.

Two important patterns were observed from the simulation outputs. First, we identified set conditions of punishment that produce more effective and less effective outputs. There were four set conditions of punishment that were consistently identified as being the most effective and another set condition identified as being the least effective at the evaluation times. Punishment consisting of 90% certainty, high or medium severity, and high celerity were identified as being most effective. Punishment with 70% certainty, high or medium severity, and high celerity performed equally and consistently well. Second, none of the most effective punishment was associated with low celerity (slow response). Punishment options consistently resulting in more than 10% vendor fraud were not associated with high celerity (fast response) except the one with 10% certainty, low severity, and high celerity.

In Figure 4, five set conditions of punishment are presented along with a baseline (one least effective and four most effective options). The least effective option only maintains or slightly decreases the current level of fraudulent vendors without further deterrence of vendor fraud. The most effective options showed a drastic reduction in the percent of vendors committing fraud after the first intervention. This was expected because of a public agency agent's continuous efforts to intervene to fraudulent vendors based on celerity in the current simulation.

<Insert Figure 4>

What Role Does Certainty Play?

We first examined the role of certainty as a mechanism for deterring fraud. For example, what role does certainty play when a public agency agent sends out different levels of sanctions 6 months or 2 years after the fraudulent vendor is caught? Figure 5 presents the effect of certainty under different set conditions of severity and celerity. In the figures, severity is consistently high, while celerity is low (Figure 5 (a)) or high (Figure 5 (b)). Each line represents a baseline (no intervention) and certainty levels (10%, 30%, 50%, 70%, and 90%). With the exception of the baseline, the lighter the line color, the lower the certainty level.

Punishment with 10% certainty performed relatively poorly in both conditions shown of Figure 5. However, celerity made a big difference for the deterrent effect of punishment even with 10% certainty. When a public agency agent intervened with only 10% of vendors behaving fraudulently after 2 years passed (low celerity), there was not much change in the prevalence of fraudulent vendors in the WIC system, even if the punishment was accompanied by high severity. Compared to a baseline without intervention, this 10% certainty option slightly decreased, but not by much. When a public agency agent quickly responded to the fraudulent vendors identified at each monitoring time, even punishment with a 10% certainty level achieved a significant reduction in the percent of fraudulent vendors in the system (Figure 5 (b)). This becomes clear when comparing the 10% certainty lines in both conditions of Figure 5.

There seem to be critical levels of certainty which bring a drastic change in the deterrent effect of punishment. For example, there is a large gap in the deterrent effects between 10% certainty and all other certainty options. Regardless of celerity levels, punishment with greater than or equal to 30% certainty performed much better than punishment with 10% certainty. Therefore, punishment with 10% certainty is least favorable unless high celerity is considered. On the other hand, punishment with 50%, 70%, and 90% certainty levels deterred fraud at very similar levels, especially when accompanied by high celerity. Once a public agency agent intervened with greater than 50% of fraudulent vendors along with other set conditions of severity and celerity, the increase in certainty brought only marginal effects in terms of deterring fraud. If the certainty of punishment is greater than or equal to 50%, one may not expect much difference in the deterrent effect of punishment by increasing certainty regardless of severity or celerity.

The prevalence of fraudulent vendors in the simulated system showed slightly different patterns of progress when conditioning different celerity levels. With low celerity, the program experienced more fluctuations in the level of fraudulent vendors due to vendors' adaptive behaviors. Slow interventions to stop fraudulent vendors allowed some risk-prone vendors to engage in fraud due to the lack of follow-up. This increases the prevalence of fraudulent vendors in a short time period, but it decreases with a subsequent intervention, as shown in Figure 5 (a). The prevalence of fraudulent vendors was more stable with high celerity because a public agency agent gave at-risk vendors less chance to commit fraud.

<Insert Figure 5>

What Role Does Celerity Play?

The role of celerity can be explained in two ways. We have reported that when a public agency agent quickly followed up with fraudulent vendors, a significant decrease in the percent of fraudulent vendors was observed in the system. In addition, celerity makes a difference in how soon a public agency agent can reduce the percent of fraudulent vendors in the system to a certain level. For example, punishment with 50% certainty, high severity, and low celerity reduced and maintained the level of fraudulent vendors at around 5% throughout the simulation. When a public agency agent implemented a punitive action with the same conditions of certainty and severity but with high celerity, the system achieved an equal level of fraudulent vendors soon after the intervention (at time 132). In other words, to reduce fraudulent vendors to approximately 5% of the system, the latter approach with high celerity may require less than two years. However, the former approach with low celerity may take much longer time.

Figure 6 further clarifies the effect of celerity with other conditions of certainty and severity. As we mentioned, a similar level of performance was observed among punishments with greater than or equal to 50% certainty, so we presented punishments only with 10% or 70% certainty. In Figure 6, three solid lines present the performance of 10% certainty options. Three lines with markers present the performance of 70% certainty options. Depending upon the level of celerity, there were large gaps in the deterrent effects among 10% certainty options in both figures. This pattern was clearer with high severity in Figure 6 (a). Punishment with 10% certainty and high celerity deterred fraud significantly in both severity conditions, compared to punishment with 10% certainty and medium or low celerity. This pattern was consistent in the 70% certainty options while the difference was getting smaller with high severity condition (Figure 6 (a)). Therefore, Figure 6 shows that celerity plays a more important role with lower certainty levels (10%) than higher certainty levels (70%) especially if high severity is conditioned. This may not necessarily be true if low severity is conditioned.

<Insert Figure 6>

How Does Severity Matter?

Figure 7 presents the simulation results with 10% or 70% certainty and low or high celerity in order to further examine the effect of severity. Solid lines represent 10% certainty options with different severity and celerity levels. Lines with markers represent 70% certainty with different severity and celerity levels. In Figure 7 (a), with 10% certainty and low celerity, the three solid lines overlap for a long time even when the severity levels differ, which indicates that severity makes not much difference in deterring fraud with the certainty and celerity levels. However, severity played a somewhat different role with 70% certainty and low celerity. In this case, the deterrent effect with different severity levels varied somewhat. On the other hand,

Figure 7 (b) shows that severity made a bigger difference in the long run with 10% certainty and high celerity conditions. Severity continues to widen the gap of the 10% certainty and high celerity options. When a public agency agent quickly responded to 70% of the fraudulent vendors caught, however, severity did not make much difference. This can be observed where the three lines with markers very closely progress in Figure 7 (b).

In the current simulation, we observed that severity might not play an outstanding role by itself, but may have a stronger effect under different time frames if a public agency agent continues to intervene in fraudulent behaviors. When a public agency agent's response to fraudulent vendors is quite delayed, then severity becomes important mainly for higher certainty options (Figure 7 (a)). When a public agency agent quickly follows up with fraudulent vendors, then severity has a greater deterrence for lower certainty options in the long run (Figure 7 (b)). Therefore, the role of severity in punishment must not only be explained by certainty, but also by celerity in a longer time period.

<Insert Figure 7>

Summary

The current simulation presents insightful patterns regarding the interplay of the certainty, severity, and celerity of punishment and provides policy guidance on a managerial decision-making to deter fraud in a complex adaptive policy system. Hodge (1991) discussed the value of a simulation that serves as an aid to thinking and hypothesizing. In this use of simulation, it is important to realize that "the model's user has only learned something about the assumptions in the model; it is arithmetic, not science" (p. 359). Therefore, we need to focus on understanding the dynamics of various set conditions of punishments rather than interpreting the numerical results of the simulation as it is. We argue that the effectiveness of a punishment needs to be understood as a balanced function of set conditions of punishment under different circumstances. The results of the computer experiments on the interplay of the certainty, severity, and celerity of punishment in deterring fraud are summarized as follows:

1. Even with higher severity, punishments with low certainty and low celerity do not deter fraudulent vendors in the system. To observe a reduction in fraudulent vendors, punishment with low certainty must be accompanied by high celerity.
2. Celerity plays a more important role when it is associated with lower certainty than higher certainty under the condition of high severity. When celerity is associated with higher certainty, it creates bigger gaps in the deterrent effects under the condition of low severity.
3. Severity becomes important when it is associated with lower certainty and high celerity in the long run. However, this is not the case when severity is associated with lower certainty and lower celerity. Severity makes varying deterrent effects with high certainty only when low celerity is conditioned.

The modeling and analytical processes used in the current paper were based on the idea of a public service delivery program as a complex adaptive system. Three autonomous actors and their decision-making interdependencies were defined, and two action rules between the participant and vendor for store choice and fraud negotiation were modeled. The level of fraudulent vendors was examined by identifying outliers in vendors' monthly sales activities. We conducted computer experiments by modeling a rule for change that represents punishments to deter fraud. We identified the most and least effective punishments based on different set conditions in the given context. The interplay of certainty, severity, and celerity of punishment was examined to generate managerial decision hypotheses in public service delivery systems.

DISCUSSION

When fraud in public service delivery programs is approached from management and policy perspectives, the traditional crime literature adds limited value in understanding the dynamic nature of illegal behaviors in a complex adaptive system or in guiding policy actions. Focusing on the nature of criminals and the causes of crime does not tell us when, how, or why the crime occurs. We framed fraud as an inevitable event when goal incongruent players of the program opportunistically behave without perfect monitoring mechanisms. As an appropriate approach to model this framework, we built an agent-based model that represents a public service delivery program in Ohio. The effectiveness of punishment was examined when different set conditions of punishments were introduced in this dynamic environment.

When one approaches fraudulent behaviors in public service delivery systems, celerity becomes a critical factor influencing the effectiveness of punishment. With lower certainty, severity may not be critical, but celerity becomes even important. For example, punishment with 10% certainty performs very differently when it is associated with high celerity, indicating that even the option can have some deterrent effects. Second, the simulation result suggested that there might be not one, but two critical certainty levels. To observe some reduction in fraudulent vendors, a public agency may need to intervene with at least 30% of fraudulent vendors identified, but interventions with more than 50% of fraudulent vendors do not bring a further noticeable reduction in the crime. Finally, the deterrent effect of severity along with certainty needs to be understood within a temporal framework. Severity may bring some deterrent effect with lower certainty in the long run, but only when celerity is high; or conversely with higher certainty in the long run, but only when celerity is low. The experiments provide us at least two important insights: (1) deterrent research needs to consider temporal contexts more seriously in order to examine the effectiveness of punishment for a policy action, if the adverse behavior occurs within a complex system, and (2) several policy options which may be equally effective can be designed based on different set conditions of punishment and used for policy actions given a public agency's goals and resources.

This research contributes to the literature in three ways. The deterrence approaches have been criticized due to unrealistic assumptions regarding human behavior (Gneezy and Rustichini, 2000; Mazar, Amir, and Ariely, 2008; Paternoster, 1987), research design flaws (Ehrlich and Brower, 1987; Paternoster, 1987; Paternoster et al., 1983), and irrelevance to policy (Mendes, 2004). Further, regulating efforts based on these studies are incompatible with the dynamic and adaptive processes that they are supposed to monitor. Consequently, policies based on this traditional approach may lead to optimization in some parts of a system at one point, but are likely to generate suboptimal performance for the system as a whole. Synthesizing the crime opportunity perspective and deterrence hypothesis within complex systems, we attempted to mediate this shortcoming and gain new insights. We modeled the certainty, severity, and celerity of punishment for adaptive behaviors within a system, analyzing the interplay of these mechanisms for deterrent effects. This process helped us to develop managerial decision hypotheses, as we summarized in the results section.

Second, it is not an easy task to study the deterrent effects of punishments in complex adaptive environments. Traditional social science research methods and tools have shown strengths in testing theories with, or calibrating patterns in, empirical data but fall short in examining underlying processes in, and actions to, such a dynamic environment. This research attempted to provide policy insights by framing and modeling fraudulent vendors in a public service delivery program. Grounded in a real public service delivery program in Ohio, we attempted to build an empirically motivated agent-based model at a relatively large scale. This robust modeling framework provides an alternative method to enhance managerial decision-making, dealing with adaptive behaviors.

Finally, this research provides useful policy recommendations for policy-makers in the context in which the model is based. While most studies have paid attention to the effect of certainty versus severity of punishment based on philosophical assumptions, decision-making in practice may require different knowledge and evidence for action in a specific decision-making setting (Mendes, 2004; Moore, 1986). For example, the simulation showed that the low certainty level of punishment would perform poorly in the current policy setting regardless of severity, unless high celerity is conditioned. Once the 50% or greater certainty level is acquired, the agency may achieve the same level of intervention outcomes. Therefore, the use of resources to increase certainty greater than or equal to 50% might not be a wise decision. Depending on the goal of the program in terms of reducing the level of fraudulent vendors, a public agency can utilize different strategies to satisfy their needs, all of which perform reasonably well.

Simulations have served as a suitable tool for decision-makers to explore possible scenarios and their consequences for a long time. ABM enhances this strength by incorporating complex interactions and interdependencies, and linking micro behaviors and macro patterns (Epstein, 2006; Epstein and Axtell, 1996; Marcy and Willer, 2002). One of the strengths of ABM that has been less highlighted is its ability to perform interactive open systems analysis for social and human systems. ABM helps not only to make a decision among alternatives, but also to frame a problem within a shared context. For example, contextual information based on the analyst's experience and an interview with practitioners has been introduced and modeled to produce context-specific policy insights. This model-building process can serve as a regular source of knowledge generation (Johnston, Kim, and Ayyangar, 2007) and multiple explanations can be tested. Therefore, the current research leveraged this strength of modeling in order to better understand the dynamics of fraud in a public service delivery program and to provide relevant guidance.

Limitations

This context-specific functionality is both a strength and weakness of agent-based modeling. The simulation was developed to model a public service delivery program in a particular context, with much of the information based on the Ohio WIC program. Revisions and updates are required when one attempts to use the framework in different contexts. Further, many parts of the simulation may require reconsideration if one attempts to use it for different types of criminal or adverse behaviors in different settings.

The simulation model can also be criticized from the standpoint of building 'realistic' models. In the current simulation, participant and vendor agents make store choices and fraud decisions immediately when they meet each other. One advantage is that some well-established models and evidence can be used to build the model. A weakness, however, is that the simulation still holds limiting assumptions regarding human decision-making. In reality, decisions may take longer, and both parties may go through the process of trial and error. Other characteristics or situations, such as historical relationships and an informal social network, may influence how decisions are made. In addition, we did not vary the level of punishment impact on risk propensity for recidivists. The deterrence effect of punishment in the case of recidivism can be separately explored and tested in another paper.

The simulation can also be enhanced by incorporating several constraints that public agencies confront, such as resources, capacity, and the legal environment. For example, the simulation identified fraudulent vendors using a risk indicator based on abnormal sales activities for the purpose of enforcing punishment. This may not necessarily be true in all cases, or public agencies may not have the capacity to monitor every transaction due to the size of public programs. Uncertainty in monitoring activities and data can be modeled and tested. Different fraudulent vendor identification methods can also be designed and tested within the dynamic environment. These limitations related to building a 'realistic, but not too simple' model are on-going discussion points in computational simulation models (Grimm et al., 2005; Starbuck, 2004).

Finally, agent-based models are developing as an alternative tool to study complex natural and social phenomena. Compared to statistical or optimization procedures, the process of building and testing the models in social sciences has not been firmly established (Richiardi, et al 2006). Several parts of the current model, such as a distribution and a change in risk propensities due to fraud involvement, are based on heuristics. While pattern-oriented modeling has been suggested as a way of addressing parameter uncertainty (Grimm et al., 2005; Wiegand et al., 2003), attention needs to be paid to the general patterns and insights identified in the simulation, rather than a strict focus on the numerical effects or levels. This limitation in modeling provides an opportunity to identify gaps in the current body of knowledge, but also serves as a challenge to build empirically motivated robust simulation models.

Table 1: Distribution of Initial Risk Propensity and Chance of Fraud Involvement for Participants and Vendors

Participants			Vendors			
Risk propensity	Number of agents	Chance of fraud involvement	Risk propensity	Number of agents	Chance of fraud involvement	
					Checkout lanes <3	Checkout lanes ≥ 3
<0.25	2,485	1%	<0.3	46	10%	5%
0.25~<0.5	3,096	10%	0.3~<0.4	28	30%	15%
0.5~<0.75	2,745	30%	0.4~<0.5	32	40%	20%
≥0.75	1,674	60%	0.5~<0.6	29	50%	25%
			0.6~<0.7	24	60%	30%
			0.7~<0.8	15	70%	35%
			0.8~<0.9	10	80%	40%
			≥0.9	16	95%	47%
	10,000			200		

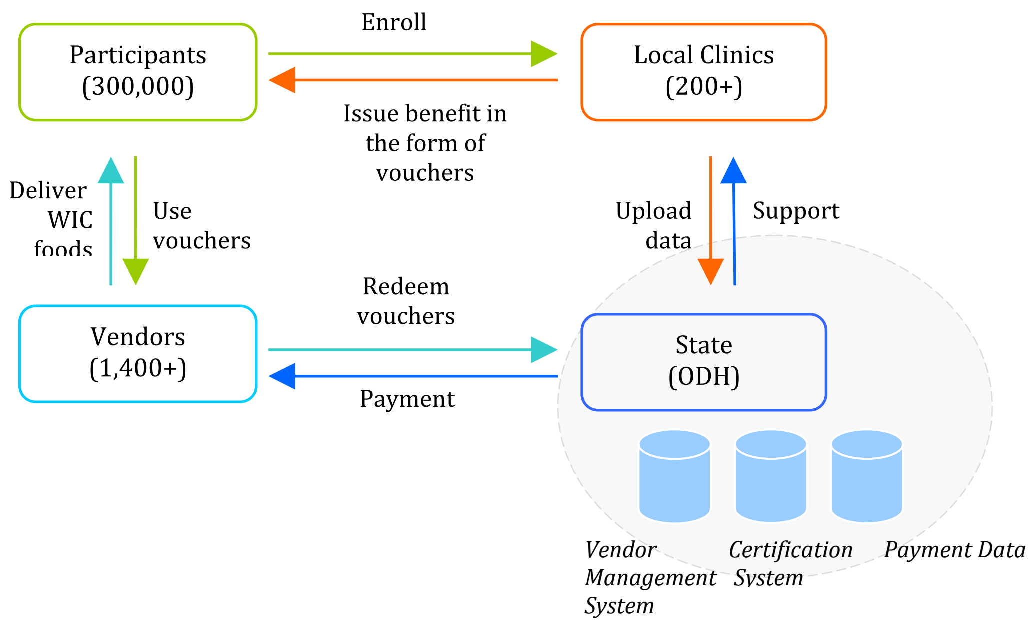
Notes:

a. Risk propensity distribution: The number of agents was generated with initial risk propensities following a truncated Gaussian distribution with a mean of 0.40 and standard deviation of 0.40, ranging from min 0.00 to max 1.00.
b. The distribution reflects two assumptions on individual decision-making when an opportunity is presented: (1) The higher the risk propensity, the higher the probability of engaging in illegal exchanges and (2) the smaller the vendor, the higher the probability of engaging in illegal exchanges.
c. This set of parameters with the rate of change of risk propensity due to decisions was calibrated by generating the baseline of vendor fraud in the system using sales activity information associated with fraud decisions.

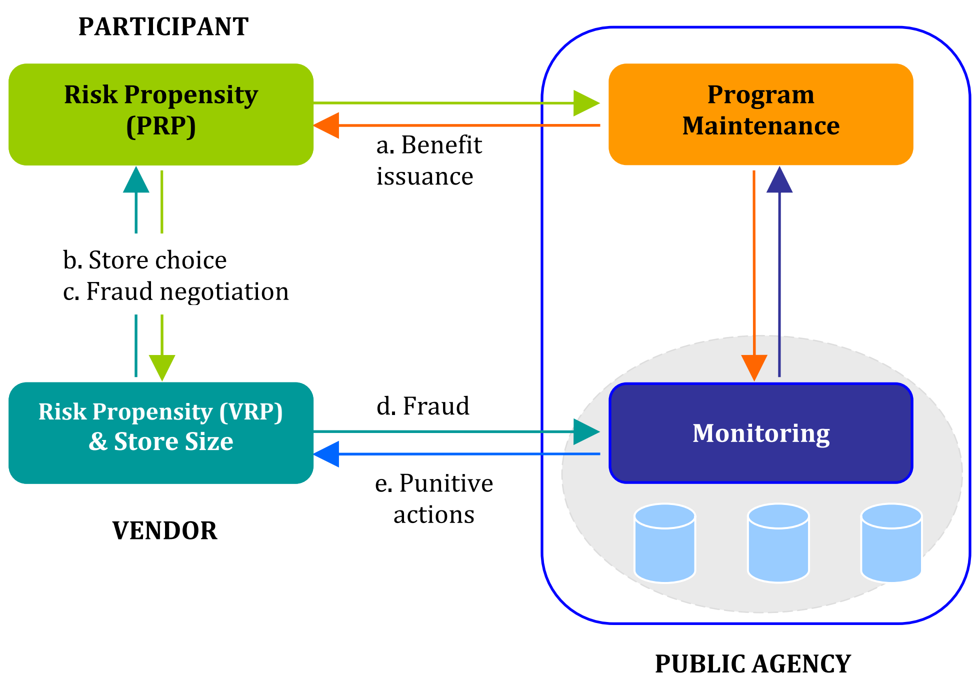
Table 2: Description of the ABM

		Description	Information	Source
	Simulation Design and Initialization			
	Agent are created at random locations with risk propensity toward fraudulent behavior	Participants = 10,000; Vendors = 200; Public Agency = 1	Hypothetical	Random Generation
	The initial distribution of risk propensity for participants and vendors in the simulated system	Mean: 0.4, Std. Dev.: 0.4, Min: 0.1, Max: 1.0	Hypothetical	
	Vendors are also randomly assigned with a number of check-out lanes	Mean: 6, Std. Dev.: 6, Min: 1, Max: 20	Empirical	Ohio WIC
	Individual Decision-making (Iteration)			
a	Public agency issues vouchers to participants	Mean: \$45, Std. Dev.: \$40, Min: \$2, Max: \$100	Empirical	Ohio WIC
b	Participants decide which vendor they will visit	Proximity and store size	Literature	Huff, 1964
c	While a participant visits a vendor, fraud opportunity is presented and participants and vendors negotiate fraudulent exchange of vouchers	See Table 1	Hypothetical	
	Not successful negotiation	Move to next choice	Hypothetical	
	Successful negotiation	Normal or fraudulent exchange	Hypothetical	
d	[Normal] The participant use a voucher within a given distribution	Mean: 75%, Std. Dev.: 10%, Min: 4%, Max: 100%	Empirical	Ohio WIC
	Those participants who are not involving in fraud, but has relatively higher risk propensity (>0.6)	They will be exposed to 1% of random chance of searching for fraud opportunity in each step	Hypothetical	
d	[Fraudulent] The vendor overcharges for the voucher from a fraudulent exchange	Record as the 100% of the face value of the voucher is used	Hypothetical	
e	A public agency identifies fraudulent vendors using a risk indicator every six months	Vendor redemption ratio (= ∑Actual sales / ∑Maximum face values at a vendor) > 90%	Empirical	Ohio WIC
e	A public agency takes punitive actions to fraudulent vendors (Computer experiment)	Punishment conditions (certainty, severity, and celerity): VRP = current VRP – severity value with different set conditions of certainty and celerity	Hypothetical	
c	The vendor received a punishment renegotiate with participants who are visiting the vendor right after the punitive action is taken		Hypothetical	
	Simulation Outputs at the Aggregate Level			
	Intervention to the system	At approximately 10% of fraudulent vendors in the system	Empirical	Ohio WIC, GAO, 1999 USDA, 2001
	Hypothesizing the interplay of punishment conditions in deterring fraud in a dynamic setting	Research objective		

Figure 1: Representation of the WIC Program in Ohio for an Agent-Based Model



(a) Business Process in Ohio WIC (Conceptual Model)



(b) Agent-Based Model of Ohio WIC

Figure 2: Process Diagram of the Simulation Model

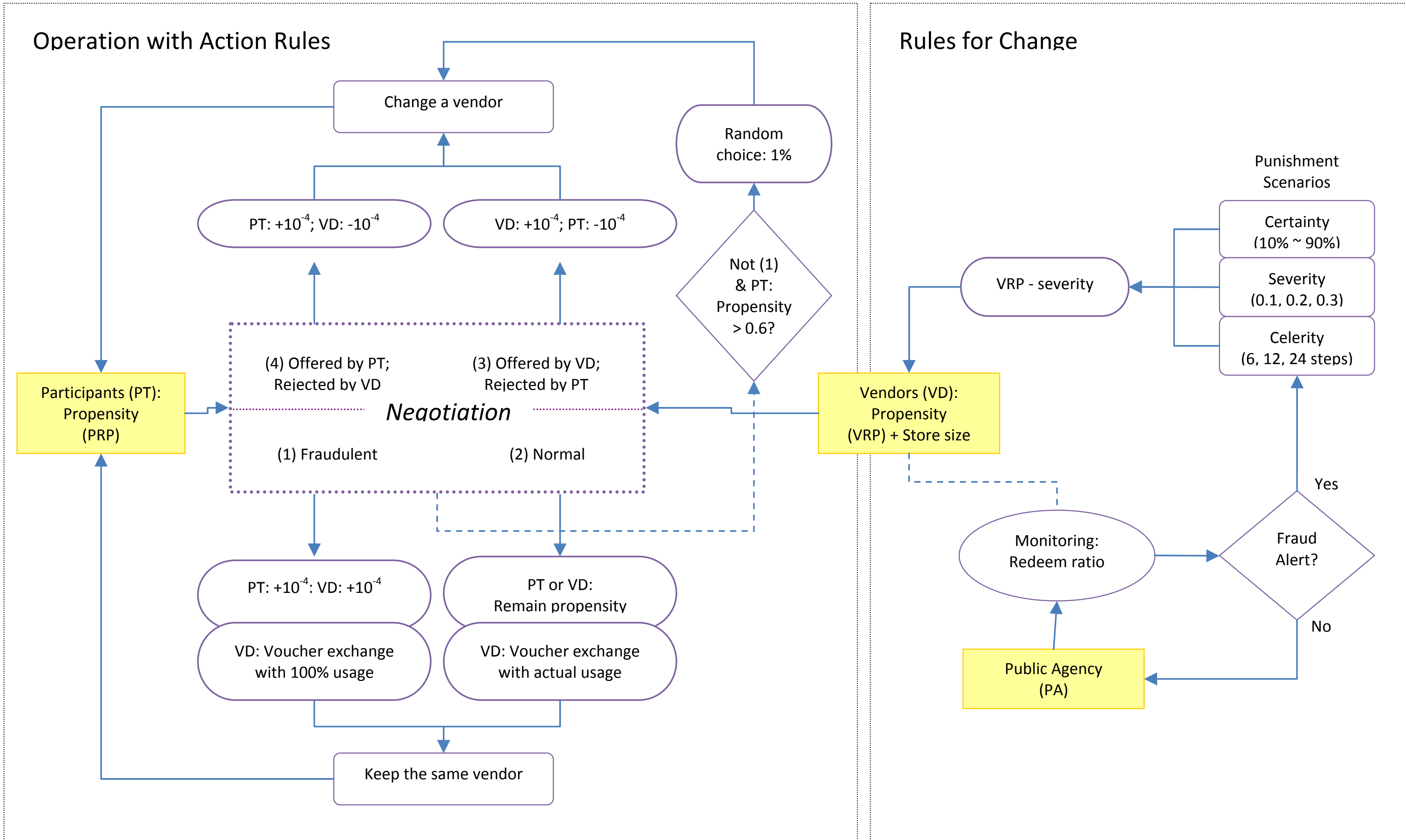


Figure 3: Percent of Identified Fraudulent Vendors by Vendor Size at Different Times

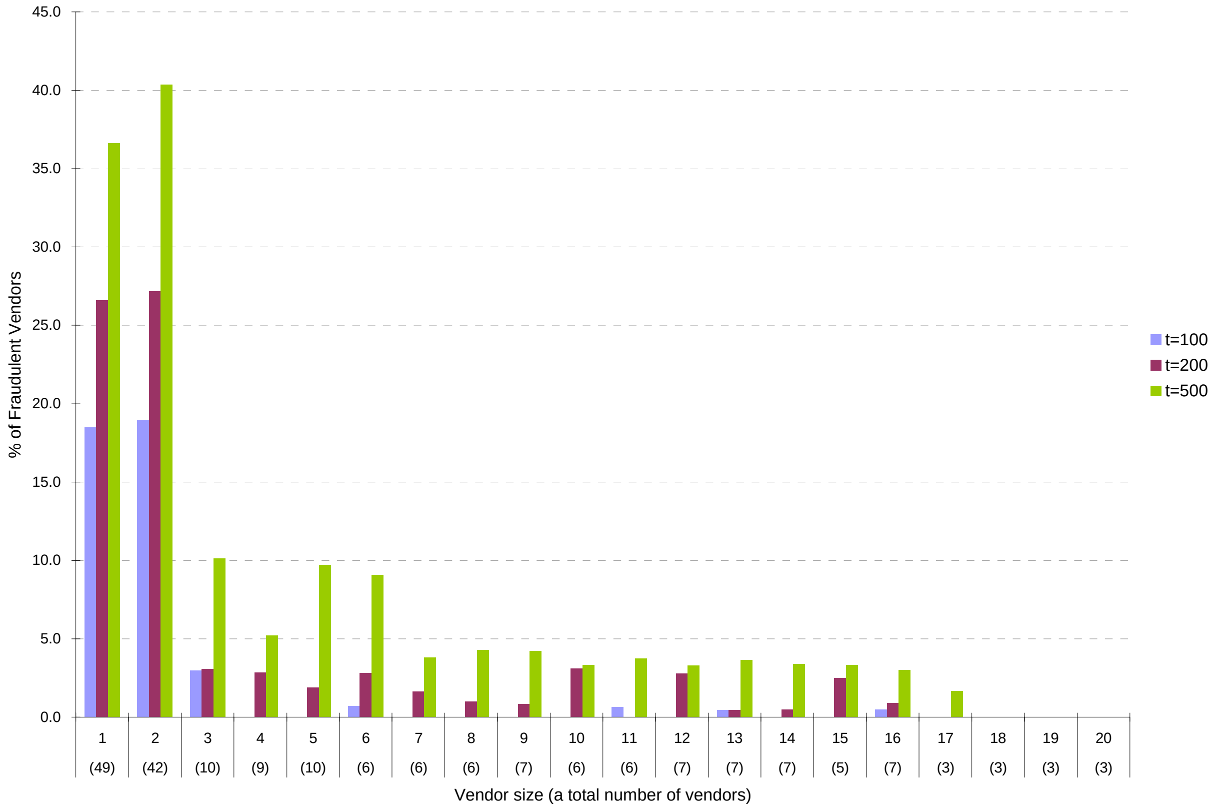
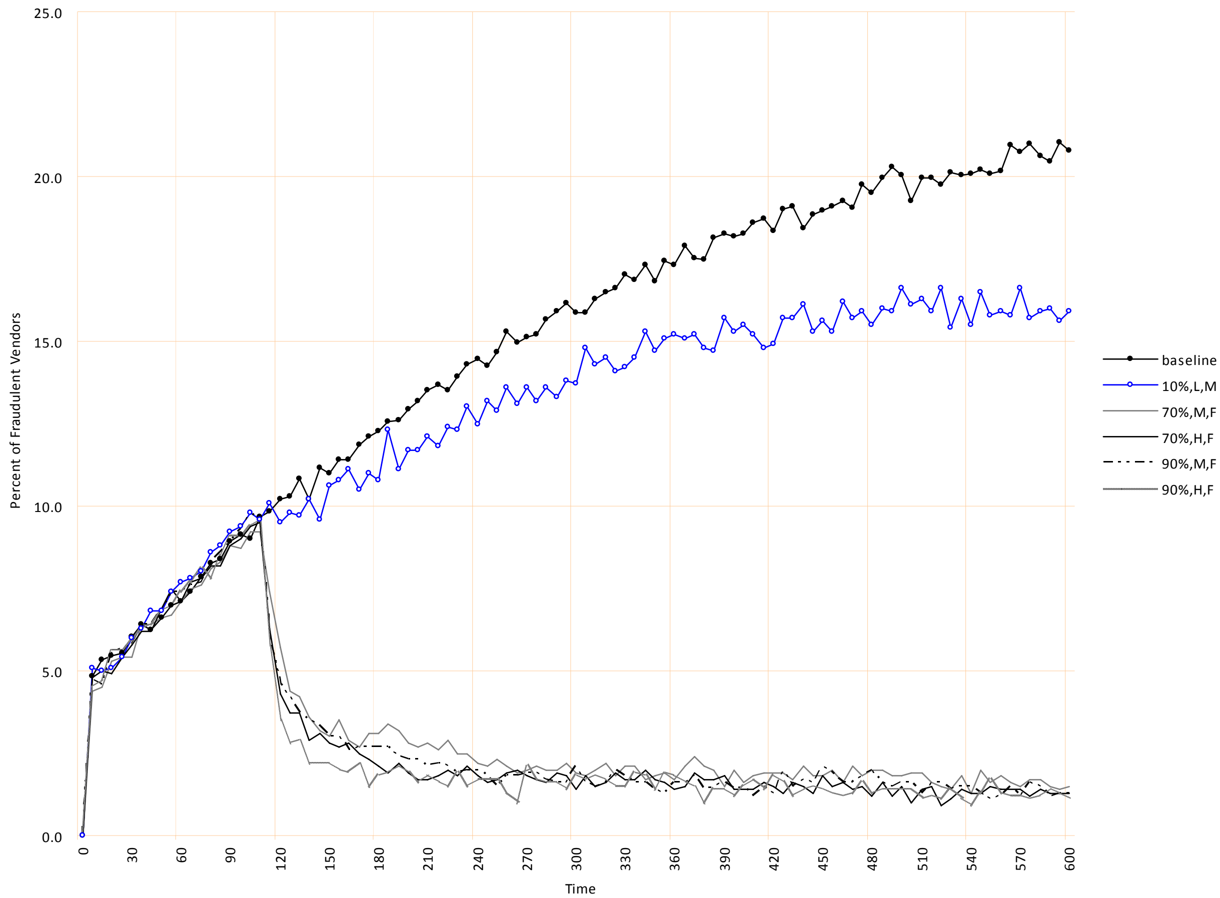


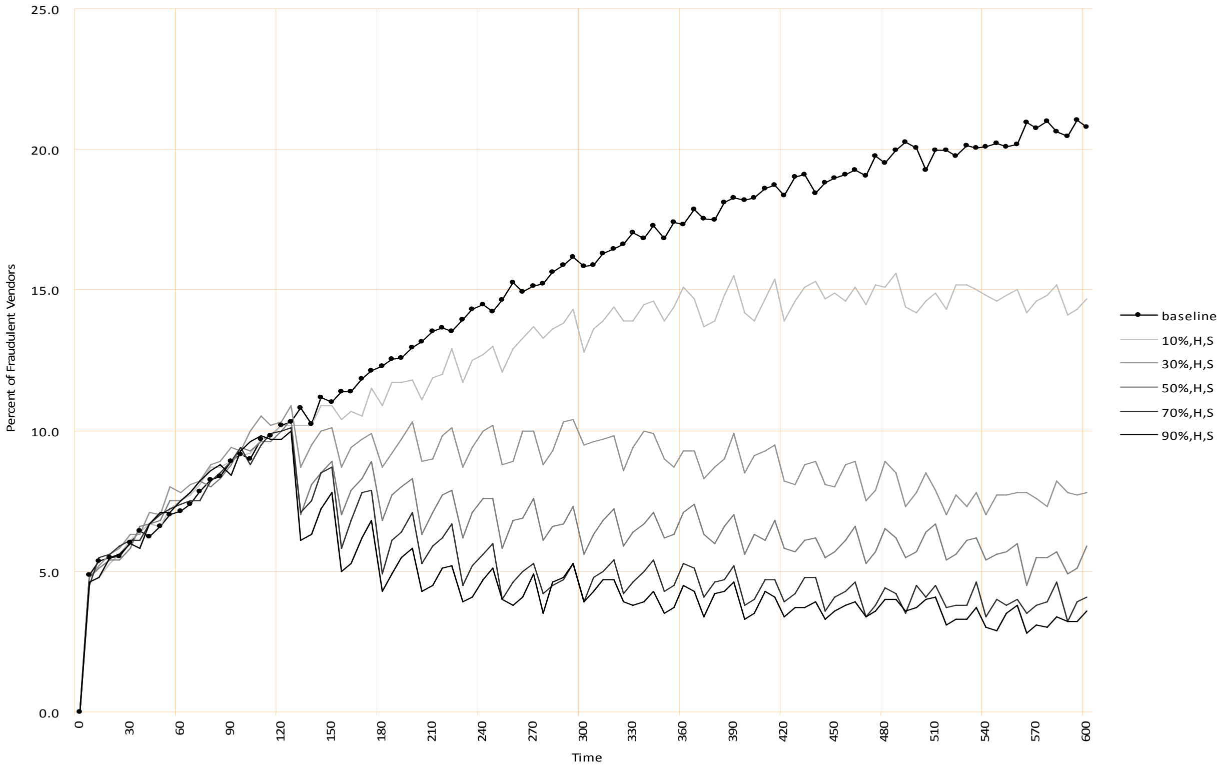
Figure 4: Most and Least Effective Set Conditions of Punishments



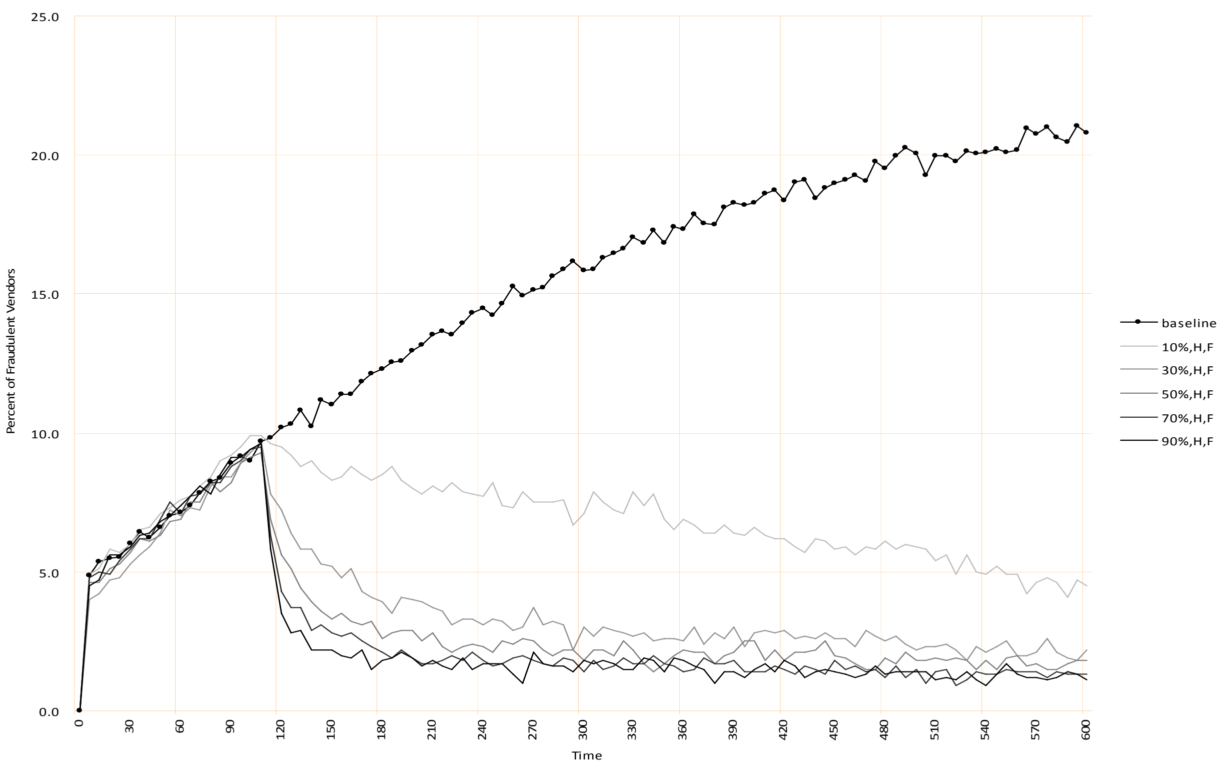
Notes:

1. We run the simulation 20 times and present the average of the simulation results.
2. Legend: (10%, L, S) implies the level of (certainty, severity, and celerity). For severity, L means low, M indicates medium, and H refers to high. For celerity, S means low celerity, M refers to medium celerity, and F indicates high celerity.

Figure 5: What Role Does Certainty Play?

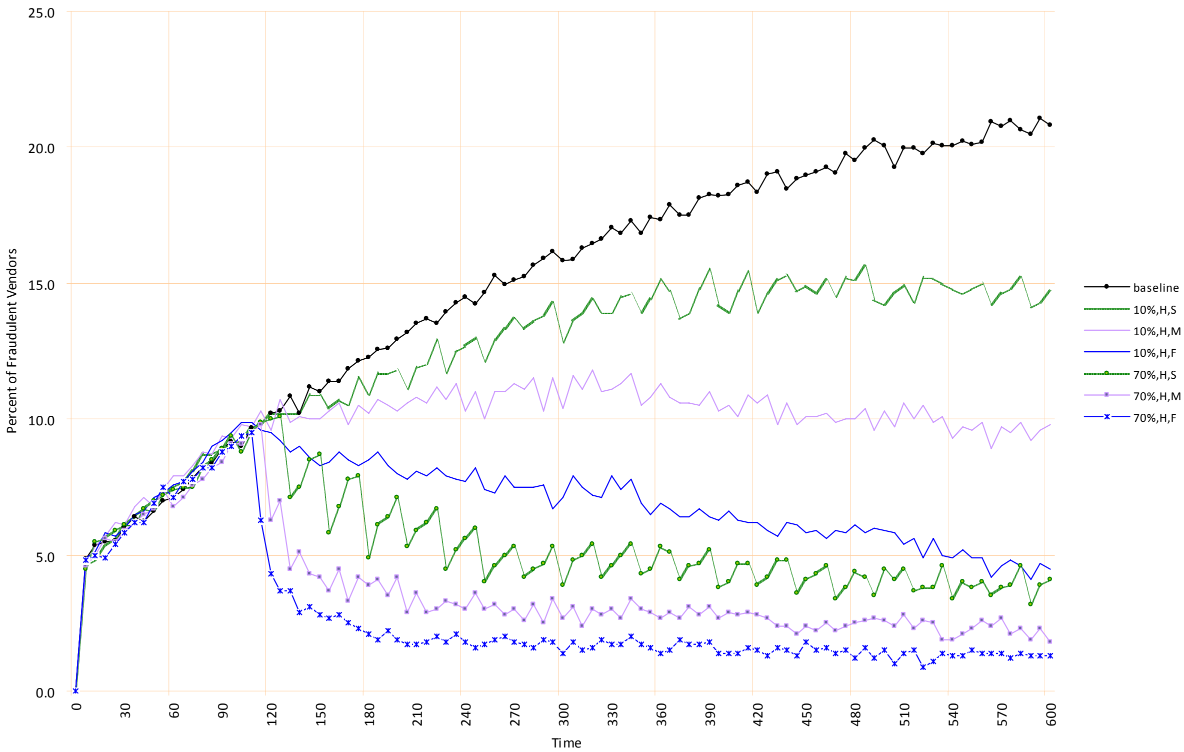


(a)

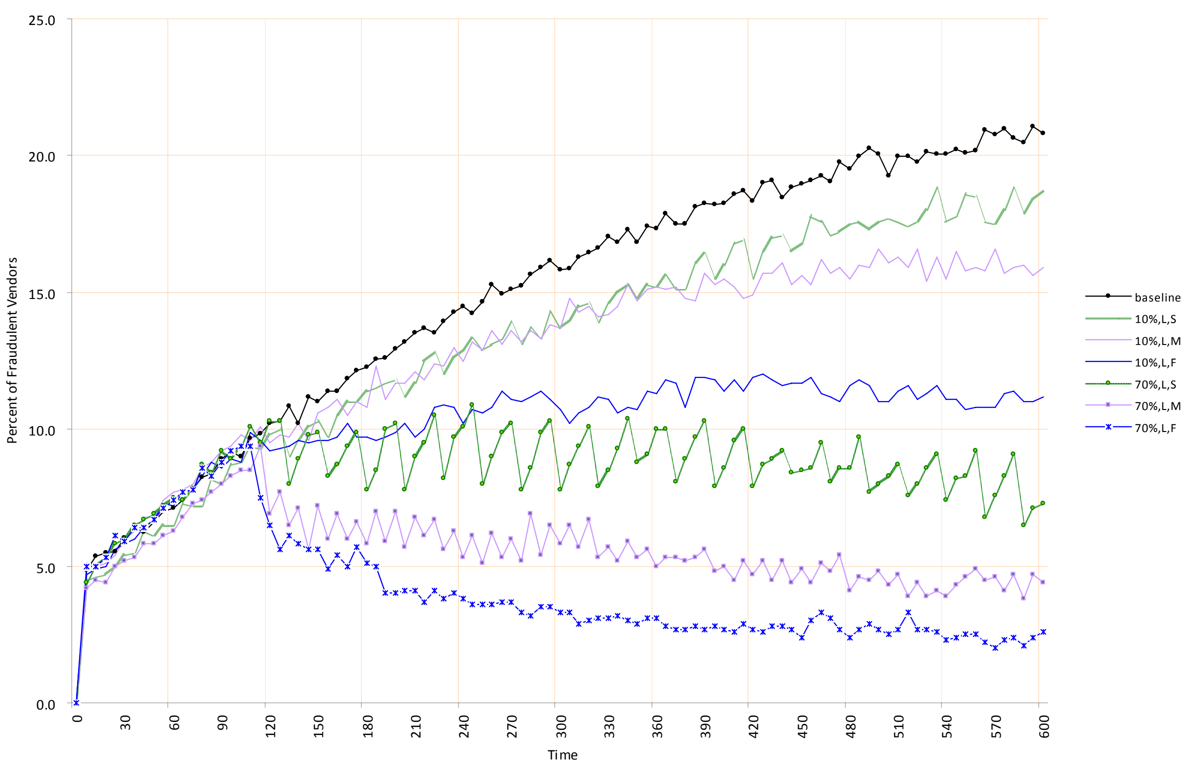


(b)

Figure 6: What Role Does Celerity Play?

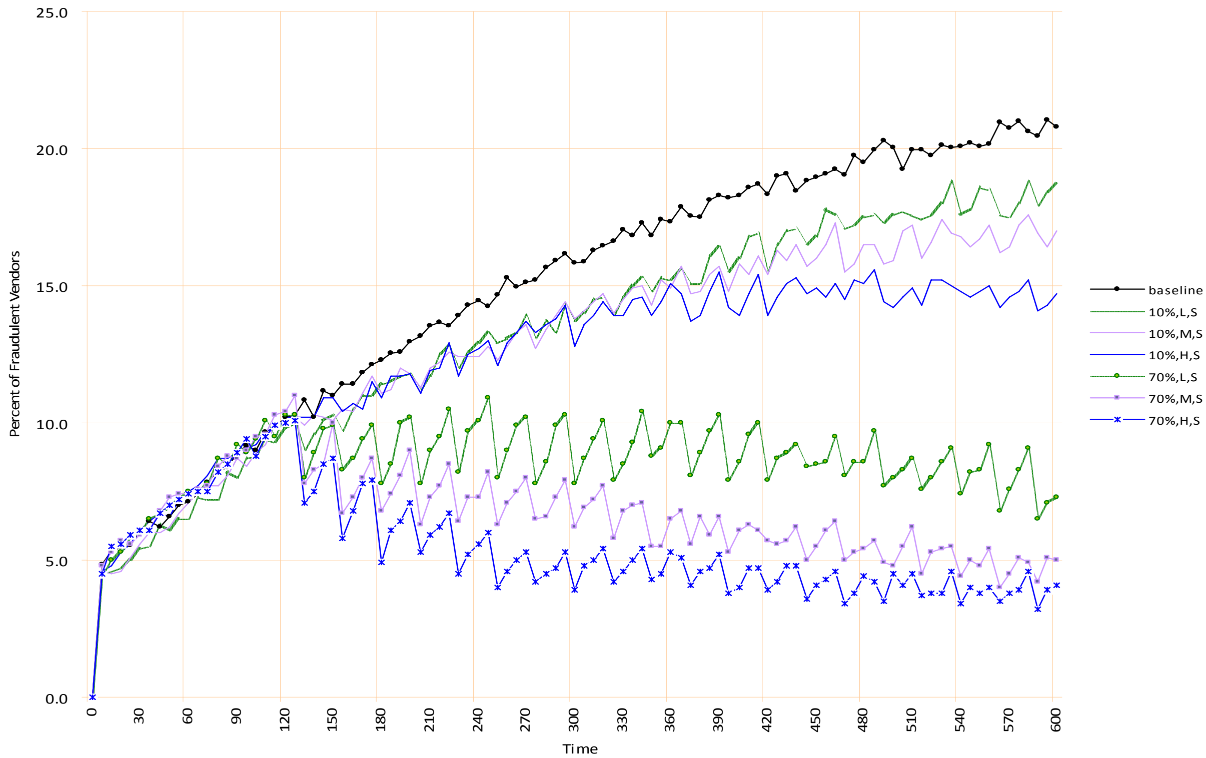


(a)

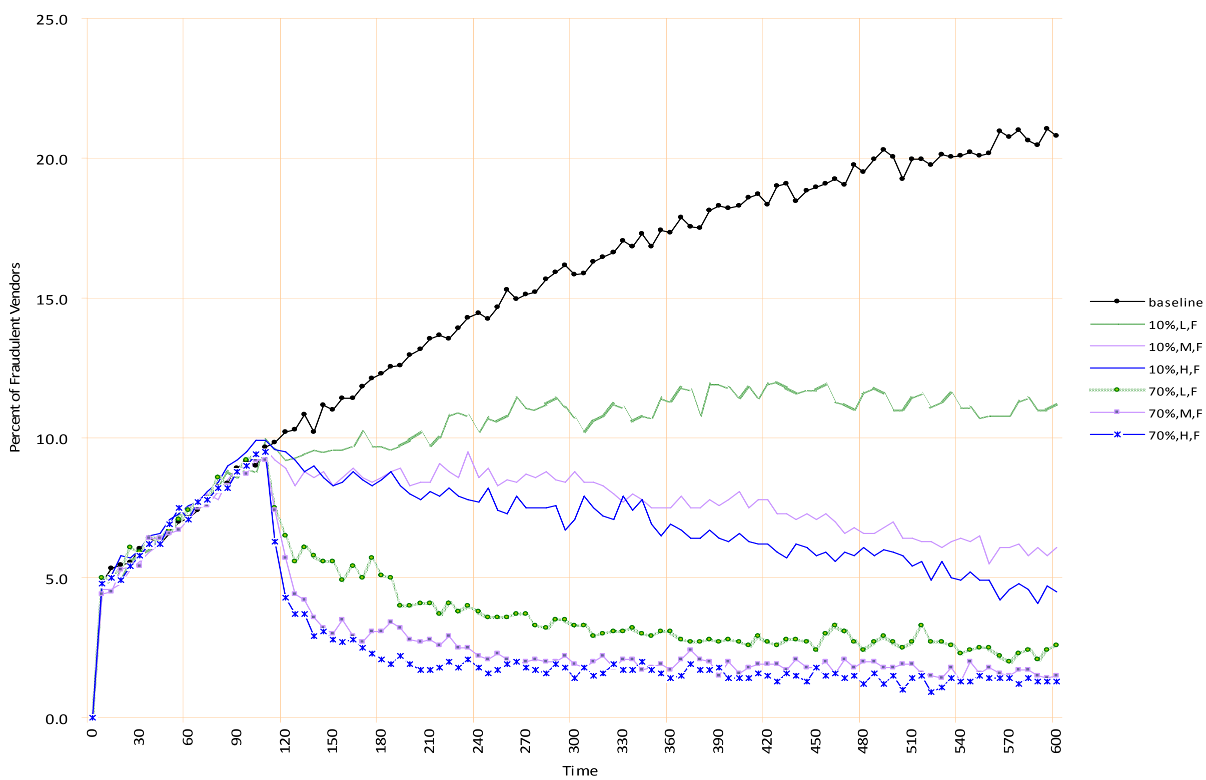


(b)

Figure 7: Does Severity Really Matter?



(a)



(b)

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