

FraudSim: Simulating Fraud in a Public Delivery Program¹

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Abstract

This chapter shows that white collar crime can be approached using an agent-based model. Fraud in public delivery programs often involves several entities that are loosely interrelated and interact dynamically. However, the crime literature has not paid sufficient attention to these characteristics, thus providing limited utility for public managers. This chapter frames a public delivery program as a complex system. The patterns of fraud in such a system are simulated using an agent-based model called FraudSim. We demonstrate that FraudSim closely replicates the statistical and spatial patterns of fraud and provides a framework for future work in this area.

Keywords: White Collar Crime, Crime Opportunity, Social Simulation

INTRODUCTION

Fraud is a crime that violates social norms, uses secretive processes, injures victims, and benefits perpetrators unfairly (Barker & Roebuck, 1973; Vandenburg, 1999). In the public sector, fraud in welfare and health care programs has been well-documented (GAO, 1998; GAO, 2005). To minimize fraud, public agencies have utilized several fraud prevention and detection mechanisms (Bolton & Hand, 2002). For example, fraud prevention focuses on procedures to avert fraud, using methods such as watermarks and personal identification documents before fraud occurs. Fraud detection focuses on identifying those who committed fraud after it has occurred using statistical methods or actual investigations. However, many of these traditional mechanisms may be static and ineffective in preventing or uncovering complex interactions among corrupt agents (Fawcett & Provost, 1997; Glover & Aono, 1995). Therefore, there is a need to develop an alternative framework to address such complex and adaptive problems in public management. In this research, we developed an agent-based model called FraudSim that can be used to simulate and analyze crime patterns in public service delivery programs. In the remainder of this chapter, we first discuss the context of our research based on a literature review of white collar crime and related issues. We then discuss our agent-based modeling framework and its implementation. This model is then tested against empirical data for the purpose of evaluation. We conclude this chapter with a discussion on the limitation and future of this research.

BACKGROUND

Traditional sociologists recognize crime to be influenced by multiple dimensions of social life. A traditional theory of criminal behavior finds criminality to be caused by poverty or the psychopathic and sociopathic conditions associated with poverty. Crime is a function of socioeconomic factors, or possibly biological factors. Criminals are similar to those who are irrational or have mental illness due to societal oppression or disease. An appropriate way to eliminate crime is to attack the root cause of crime through job creation and income maintenance (Cooter & Ulen, 2000).

Sutherland (1940) argued that the traditional conception of crime and explanations were misleading and incorrect. He argued that the traditional theory was derived from data provided by criminal justice agencies, which focused on lower class crime. A general theory of crime should include white collar crime, and white collar criminality is not different from the criminality of the lower class. Both types of criminality are *learned* rather than simply influenced by the psychopathic and sociopathic conditions.

While Sutherland (1940) provided a compelling view of criminality as learning behavior regardless of social class, white collar crime has primarily been interpreted as crime committed by a person of respectability and high social status in the course of his occupation (Baker, 2004; Braithwaite, 1985). White collar criminals are mostly recidivists, and their illegal behavior is much more extensive. They often do not lose status among associates, even after violating the laws designed to regulate business (Sutherland, 1982). However, the usefulness of the distinction of crime by social status has been a source of debate in crime theory (Griffin, 2002; Hirschi & Gottfredson, 1987; Lynch, McGurrin, & Fenwick, 2004). Empirical studies on social class and punishment have also yielded mixed results (Benson & Walker, 1988; Wheeler, Weisburd, & Bode, 1982).

The current definition of white collar offenses by the Department of Justice shows that it constitutes those non-violent illegal activities, which principally involves traditional notions of deceit, deception, concealment, manipulation, breach of trust, subterfuge, or illegal circumvention (Baker, 2004). Levitt & Dubner (2005) argued that “despite all the attention paid to rogue companies like Enron, academics know very little about the practicalities of white collar crime” (p. 46). Friedrichs (2004) suggested an integrated theoretical approach, describing cases such as the Enron scandal as “an outcome of a complex interaction of many different factors and variables, operating on various levels” (p.116).

Crime Opportunity

A group of criminologists has focused on crime as events and actions. The studies rooted in routine activity theory are interested in spatio-temporal dynamics of crime (Cohen & Felson, 1979; Felson, 1994). Routine activity theory is a micro-level theory and 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 (Felson, 1994; Eck, 1995). These recurrent and prevalent activities deliver crime opportunities to the offender (Cohen & Felson, 1979; Felson, 1987). Place is also central to this theory, facilitating or inhibiting crime as a crime promoter (e.g. abandoned building) or a crime suppressor (e.g. place manager).

Routine activity theory may predispose some persons to greater risks as targets or to greater motivation as offenders. The theory frames that the selection of a particular target within a socio-temporal context is determined by the expected utility of one target over another (Miethe & Meier, 1990). However, Osgood, et al (1996) argued that “this sharp distinction between offender and victim is not applicable to a large share of illegal or deviant behavior” (p. 636). The motivation for deviant behavior is inherent in the situation rather than in the person. To participate in illegal or deviant behavior, one needs to be there when the opportunity arises and when others are willing.

Building a Framework from a Management Perspective

The literature offers substantial accounts of the nature and causes of criminality and crime. However, it is rare to see the literature that has paid attention to the mechanisms underlying the practice of fraud, particularly in public delivery programs, where several entities are dynamically and loosely interrelated (Weick, 1979). Public delivery programs consist of interdependent, but incongruent entities. They pursue different goals while working together. For example, public agencies attempt to efficiently deliver public services to recipients by frequently contracting with private entities. While these private entities are responsible for delivering the services on behalf of public agency, they also attempt to maximize profit from the delivery. Program recipients are supposed to improve their physical/economic conditions by complying with program policy and consuming the services. Public services are designed and delivered through routine procedures among these players under the assumption that each player will comply with policy for the common good. In reality, however, policy intention is not implemented as designed. For example, fraud occurs when some players who have specialized access behave opportunistically in order to take an advantage of a system.

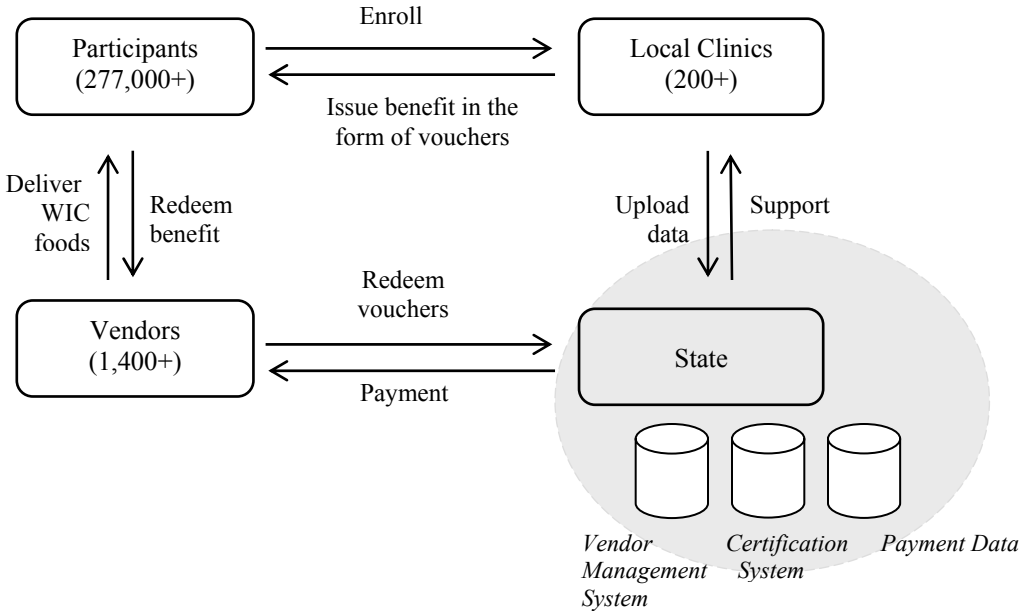
Given the characteristics of public delivery programs, Sutherland's view on criminality and crime opportunity together provide a useful theoretical framework to explore fraud. It is our contention that the players are vulnerable to the temptation to commit fraud in the policy system and there is no sharp distinction between those who will be involved in fraud and those who will not. Some individuals are more likely to succumb to temptation than others depending upon their propensity toward illegal behavior. Further, we claim that noticeable spatio-temporal macro patterns emerge from the routine activity and opportunistic behavior of individual players at micro-levels.

A few scholars have recently attempted to understand fraud as outcome of complex interactions (Friedrichs, 2004; Provost, 2002; Wilhelm, 2004). They recognize that fraud is an issue that requires a dynamic, evolving, and adaptive approach due to its complexity. However, the adaptive nature of fraud is not well-addressed in traditional frameworks. It requires a dynamic and equally adaptive approach. Spatio-temporal patterns need to be carefully considered in order to effectively address the issue. Recent advances in complexity science see natural, human, or social phenomena as complex adaptive systems. Complex systems consist of a network of interacting adaptive agents who exhibit a dynamic aggregate behavior emerging from individual activities of the agents (Holland & Miller, 1991). Agent-based models have been developed as operational models of this approach (Banks, 2002; Epstein & Axtell, 1996). This model provides a solid methodological framework to examine our contention.

METHODS

The Special Supplemental Nutrition Program for Women, Infants, and Children (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. In Ohio, WIC serves approximately 277,000 participants each month with a budget of over \$150 million each year. Ohio WIC has contracts with over 200 local clinics and 1,400 vendors. These participants, local clinics, vendors, and the state agency are the major players in Ohio WIC. Because the operation of WIC is mainly at state and local levels, we do not consider federal government in this research.

Figure 1 illustrates the business model of the Ohio WIC program. Each month, participants receive three or four vouchers with food benefits at local clinics. These participants are expected to redeem their benefits at WIC retail vendors within a specified period. These vendors are convenience marts or national grocery chains. When they receive their vouchers, participants are informed available vendors for their use within their county. Each voucher specifies the products and quantities a participant can purchase, as well as the maximum prices that the state will pay for an allowable food. The state pays for the vouchers collected from the vendors. The state also monitors the overall flow of transactions in the WIC system.



Note: The figure shows how players in Ohio WIC interact. Numbers inside boxes present how many participants, local clinics, and vendors are of Ohio WIC.

Figure 1: Business mechanism in Ohio WIC

The WIC program is subject to managerial and operational breakdowns and their undesirable consequences. Fraud can significantly contribute to such a breakdown. Fraud has been detected among vendors (approximately 9 percent of all vendors), participants (0.14 percent), and employees (4 percent) (GAO, 1999).² This shows that fraud in public programs is not committed by any specific player. Although they were not supposed to be involved in illegal activities, all players are vulnerable to the temptation to commit fraud. In addition, the reality of fraud in public delivery programs is more complex.

In the WIC program, four possible fraud mechanisms can be noted. First, fraud can occur through illegal exchanges of benefit between vendors and participants. For example, vendors overcharge when participants redeem their benefits. Some other illegal activities include forcing a participant into unwanted purchases, substitutions of WIC foods for unauthorized items (substitution), and exchanges of public service benefits for cash (trafficking). Second, fraud can occur through the improper exchange of benefits among participants, though the WIC policies and guidelines require that they do not hand over the benefits to non-WIC participants or other WIC participants. In reality, compliance on this contract is uncertain in some cases. Third, fraud can also occur through a network of corrupt vendors. In addition to all these improper conducts, there is a chance that a third party can be involved.

While other mechanisms are relevant, the focus of this chapter is placed on fraud committed by the interactions between vendors and participants because these are more common in the WIC system than other types of fraud. An agent-based model is developed to capture macro patterns emerged from their interactions. The simulated crime patterns are compared with the observed in an empirical dataset.

Data

For a case study, one month of payment data from an Ohio county were examined to obtain an estimate of the distribution of the risk status of vendors. Vendors are a key target to be monitored in terms of fraud. In the sample county,³ a total of 188 vendors were included, along with a total of 28,887 participants who redeemed their benefits in April 2004.⁴ On average, a vendor has 6 checkout lanes, ranging from 1 to 30 lanes. The state paid, on average, \$8,976 to each vendor while the total cost from collected vouchers was an average of \$11,589 at each vendor. The vendor redemption ratio was approximately 82 percent of the state's voucher costs. Average WIC sales per checkout lane were \$2,520 per month. Average food costs per participant at the vendor were approximately \$40, ranging from \$7 to \$76. This information is provided in Table 1.

Here we focus on the pattern of WIC sales volume in order to identify vendors who involve in fraud or have a high potential of committing fraud. WIC sales volume is investigated for (1) vendor redemption ratio (state payment to vendors / voucher costs), (2) WIC sales per checkout lane (state payment to vendors / checkout lanes), and (3) food package costs per participant at the vendor (state payment to vendors / participants per vendors). These indicators are based on a data-driven risk assessment in the state system that serves to identify outliers (i.e., over 90th percentile for each indicator). In the state vendor monitoring system, vendors meeting more than one risk indicator (out of three) are considered to be high risk. The percent of vendors identified as outliers by each indicator is also reported in Table 1. The information from the empirical data is used as a reference for the following simulation model.

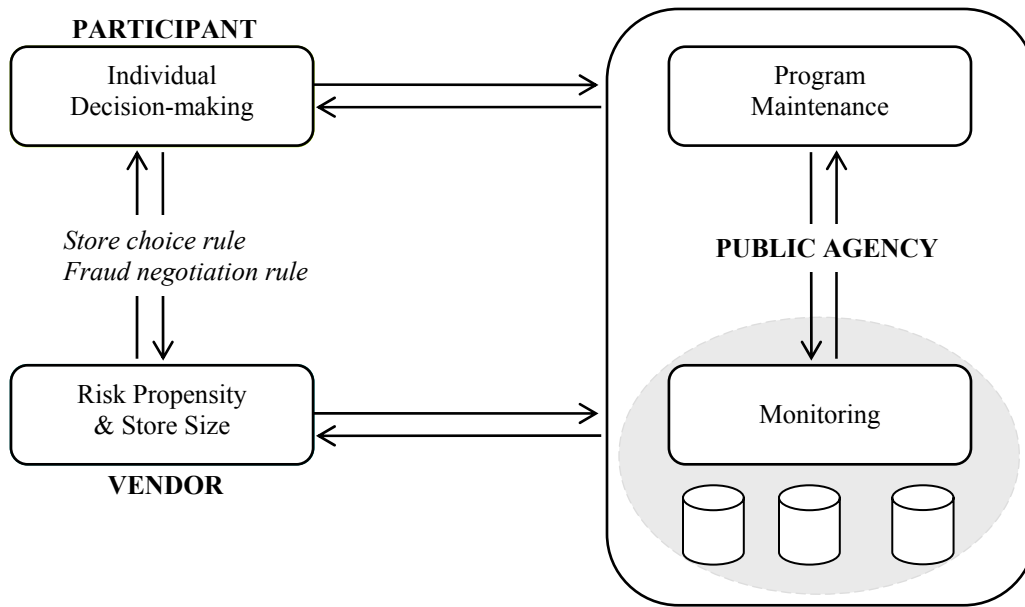
Table 1: Descriptive statistics in a WIC county in Ohio in April 2004 (number of vendors = 188)

	Mean	Std. Dev.	Min	Max	Note ^a
Checkout lanes (#)	6	6	1	30	
State payment to vendors (\$)	8,976	10,008	28	56,884	
Voucher costs (\$)	11,589	13,988	38	82,263	
Participants per vendor (#)	223	248	4	1,402	
<i>Risk indicators</i>					
Vendor redemption ratio (%)	82.0	10.7	60.0	100.0	6.4%
WIC sales per checkout lane (\$)	2,520	2,706	3	16,673	9.6%
Food costs per participant at vendors (\$)	40	12	7	76	8.5%

^a Percentage of vendors who met each risk indicator

FraudSim: Agent-Based Modeling

FraudSim is developed within the programming structure of MASON⁵ that serves as the basis for a wide range of multi-agent simulation tasks (Balan et al., 2003; Luke et al., 2004). Players in Figure 1 are modified and used as basic agents. In Figure 2, agent “public agency” provides the functions of local clinics and state administration, such as program maintenance and monitoring. A “vendor” agent is responsible for delivering food and nutritional supplements to “participant” agent, who redeems their vouchers. The public agency agent is not spatially explicit, while the other types of agents are spatially referenced.



Note: The figure defines agents, interdependency, and interactions for an agent-based model of the Ohio WIC system. Capital letters represent agents and italics show interaction rules.

Figure 2: The framework of FraudSim for Ohio WIC

In terms of key properties, risk propensity and vendor size are crucial on which this chapter focuses. Risk propensity is a hypothetical property used to model the change of an agent’s propensity toward risky behavior. It is assumed that at the initial stage, agents’ risk propensity follows a truncated Gaussian distribution with a mean of 0.40 ranging from min 0.00 to max 1.00 for both participant and vendor agents, regardless of other properties. The assumption is that the higher the assigned risk propensity, the higher the probability of committing fraud will be.

In the simulation, vendors’ involvement in fraud is influenced by store size and dynamically changing risk propensities. Store size is a proxy of business type in the WIC program. 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 than among large vendors (USDA, 2001). Hence, the smaller the vendor, the larger the probability of

committing fraud. For example, among small vendors (< 3 checkout lanes), if risk propensity is greater than 0.9, there is a 95 percent chance of committing fraud, while if risk propensity is less than 0.3, the vendor has only a 10 percent chance of being involved in fraud. For larger vendors (> 5 checkout lanes), those with a low risk propensity (< 0.3) have a 0.01 percent chance of participating in fraud, while vendors with a high risk propensity (> 0.9) have a 10 percent chance of committing fraud. This process will lead to a skewed distribution of vendor risk status by store size over time. In other words, smaller vendors with high-risk propensity will become a high risk vendor over time because they have a higher chance of being involved in fraud, even when risk propensity was equally distributed among the vendors at the initialization.

Interaction Rules

Two interaction rules were designed for the simulation: (1) a store choice rule and (2) a fraud negotiation rule. During the initialization of the simulation model, each participant is assigned a vendor. This assignment is based on the store choice rule that is adopted from the spatial interaction model developed by Huff (1964), which provides some sense of how participants will choose vendors upon joining the program, as well as in general. In the Huff model, the probability of a consumer visiting a particular store is calculated as a relative measure equal to the ratio of the utility of that store to the sum of utilities of all stores considered by the consumer. More formally, $p_{ij} = \frac{U_{ij}}{\sum U_{ij}}$, where i and j indicate the consumer and store,

respectively. The utility (U) consists of two decision factors for store choice, store size of j (S_j) and distance between i and j (D_{ij}). In the original Huff model, store size is measured using store footage. Here, the number of checkout lanes was used as a proxy of store size. Euclidean distance was measured between the locations of participants and vendors. Using this rule, participant agents will show their preference on vendor selection.

Once theoretical store choice is identified using the store choice rule as a base, a fraud negotiation rule is executed. During each iteration, a participant agent visits a selected vendor agent. Then, randomly selected participants are exposed to fraud offer by vendor agent. They negotiate fraud depending upon the result of a coin toss. The result of the coin toss is influenced by their risk propensity. Agents with high risk propensities will have higher chance to have a decision of involving in fraud. Fraud negotiation between participant and vendor agents results in two possible outcomes depending upon their agreement. If both agents agree to commit or not commit fraud at the initial contact, then participant agents continue to visit the vendor and use their benefits throughout the simulation. Individuals do not make rational choices all of the time, so randomness is introduced for some participants who have high-risk propensity but are not involved in fraud by chance. Participant agents who were not involved in fraud, but have a relatively high risk propensity (> 0.6), will have a 1 percent of chance of moving to random vendors during each step. The participant agents run the fraud negotiation rule with new vendors until they find a comparable vendor. When one party refuses to be involved, fraud negotiation fails. In this case, participant agents move to the next vendor selected by the store choice rule and run the fraud negotiation rule again.

Voucher Exchange and Fraudulent Behavior

Along with the interaction rules, three voucher exchange and recording behaviors were identified to simulate vendors' sales activities. First, the public agency agent issues vouchers, each with a mean of \$45.00 and ranging from \$2.00 to \$100.00, to participant agents. A

participant agent uses approximately 75 percent of the voucher value, with a range of 4 to 100 percent, when exchanging the vouchers for WIC foods. Voucher issuance and benefit exchange for participants at vendors are probabilistically decided within the given ranges.

Second, actual dollar amounts used by participant agents will be recorded differently, depending on the result of the fraud negotiation. If a participant agrees to commit fraud, it will be recorded that the participant used 100 percent of the benefit. For those who are not involved in fraud, the actual amount used by participants will be recorded. Therefore, actual sales amounts are manipulated depending upon the outcome of the fraud negotiation.

Third, the risk propensities of participant and vendor agents will change, depending upon their decisions and behaviors. It is assumed that risk propensity increases or decreases faster for smaller vendors than larger vendors when they are involved in fraud. Based on these basic assumptions, multiple parameters were tested and revised to identify appropriate sets that closely replicate the statistics from the empirical data. The initial parameters for the basic properties are summarized in Table 2.

Table 2: Initial parameters of the basic properties used in the simulation

	Mean	Std. Dev.	Min	Max
Vendor risk propensity (VRP)	0.40	0.40	0.00	1.00
Participant risk propensity (PRP)	0.40	0.30	0.00	1.00
Voucher values (\$)	45.0	40.0	2.0	100.0
Voucher usage by a participant (%)	0.75	0.10	0.04	1.00

SIMULATING FRAUD PATTERNS USING FRAUDSIM

Here, the focus is placed on simulating the statistical and spatial patterns of fraud in the policy system using FraudSim. Though a simulation does not prove anything, it can be used to produce data for evaluation and investigation. Using the simulated data based on the assumptions above, statistical patterns are examined first. Spatial patterns are discussed later.

Replicating Descriptive Statistics

To make this simulation tractable, the size of the WIC system was reduced to 20 vendors and 1,000 participants. The simulation was repeated 10 times; each time, the properties of the vendors and participants were randomly generated using the probability distributions described in Table 2. The results of FraudSim exhibit similar store size distribution over multiple runs.

Based on our assumptions, small vendors with a high-risk propensity are more actively involved in fraud. This results in a higher sales volume for some small vendors and, ultimately, more vendors with high-risk status among these small vendors at the end of the simulation. The majority of vendors and participants will not be involved in committing fraud, especially at larger vendors.

A dynamic aspect of the WIC program is also considered in the simulation. For example, Ohio WIC has existed for over 30 years. The pattern of risky vendors in one county in April

2004 only provides a snap-shot of the long history of the program. Therefore, statistics in the empirical data reflect only a case in a certain point in time. This chapter is interested in replicating the snap-shot using the simulation. For this, the simulation stopped at Time 299, and simulated data are examined in order to be compared with the results of April 2004.

Descriptive statistics of the simulation at Time 299 were reported in Table 3. The absolute sales amounts are approximately 1/10 of the original size of the WIC business in the empirical data with similar distributions. In the simulated data, vendors redeemed approximately 82 percent of the total voucher costs. Given that the average voucher usage of participants is 75 percent at the initialization (Table 2), the vendor redemption ratio increased throughout the simulation. A major source of this increase is fraudulent vendors' sales manipulation behaviors. This also inflates the value of the other indicator, food costs per participant at each vendor, which measures how much food a participant redeemed at vendors. On average, food costs per participant at vendors were \$40, ranging from \$11 to \$78. Given the fact that average voucher values in the simulation are \$45 and the usage by participants is approximately 75 percent of the value, it is expected that food costs per participant would be approximately \$33 where there is no fraud.

Table 3: Descriptive statistics in the simulation at Time 299 (number of vendors = 200)

	Mean	Std. Dev.	Min	Max	Note ^a
Checkout lanes (#)	7	6	1	20	
State payment to vendors (\$)	1,070	964	0	4,594	
Voucher costs (\$)	1,362	1,298	0	6,043	
Participants per vendor (#)	28	26	0	122	
<i>Risk indicators</i>					
Vendor redemption ratio (%)	82.2	8.8	65.2	100.0	11.0%
WIC sales per checkout lane (\$)	313	359	0	2,158	10.0%
Food costs per participant at vendors (\$)	40	8	11	78	10.5%

^a Percentage of vendors who met each risk indicator

Figure 3 presents the distributions of the sales by the three indicators. The distribution of the empirical data in April 2004 is presented on the left, and the distribution of the simulated data at Time 299 is presented on the right for comparison. The largest difference was found from the vendor redemption ratio. However, this figure shows that, overall, the simulation closely replicates the distributions of WIC sales by the three indicators in the empirical data.

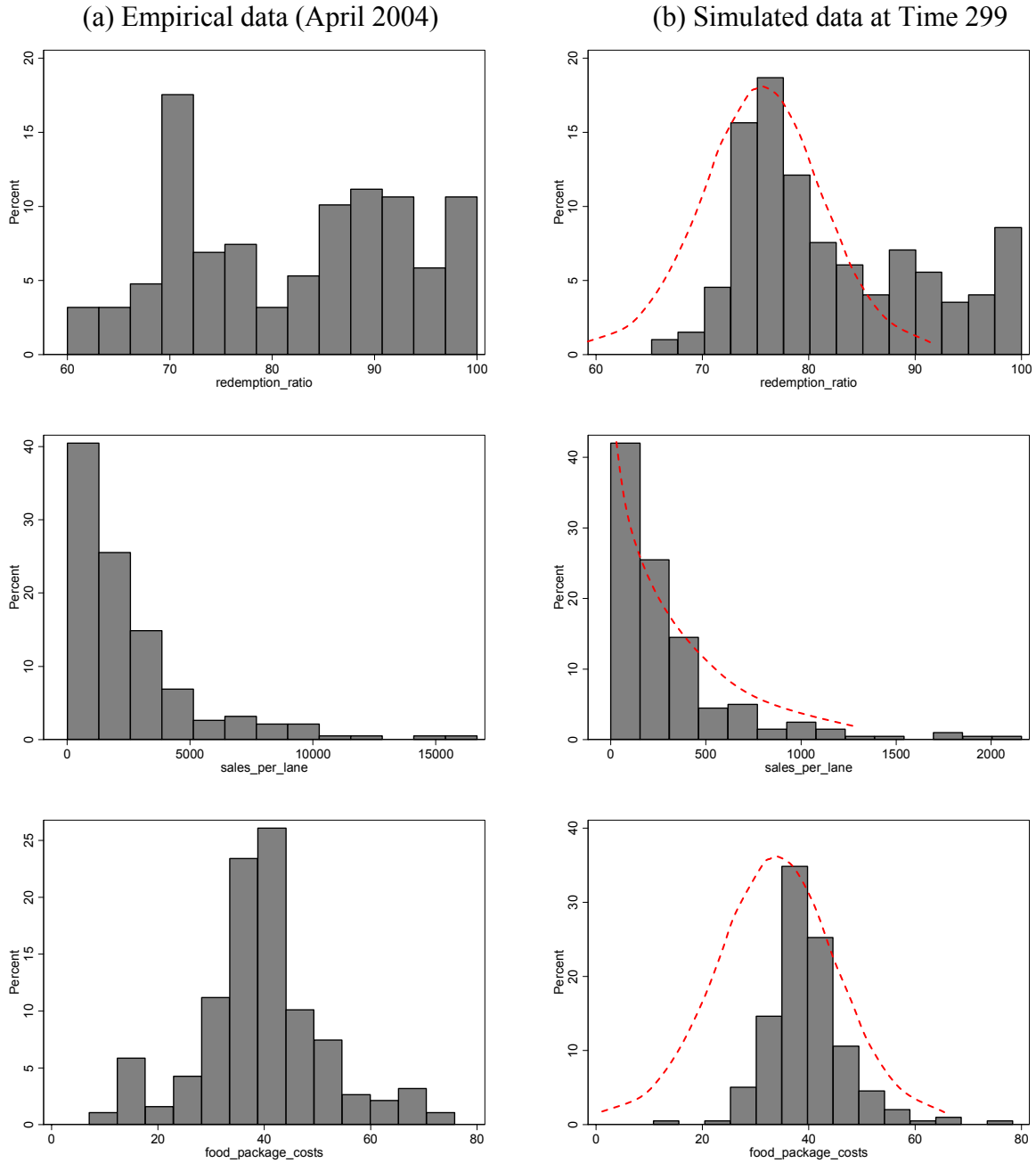


Figure 3: Distributions of sales activities by three risk indicators: vendor redemption ratio, sales per checkout lane, and food package costs per participant

While Figure 3 shows the distribution of WIC sales activities by different monitoring indicators, two questions still remain. The first question is whether the simulation replicates the distribution of high-risk vendors in the empirical data when the individual risk indicators are combined. In other words, the state categorizes vendors as high-risk when two of the three indicators are met at the same time. Therefore, it is expected that the simulation needs to generate a similar distribution of high-risk vendors. The other question is who the outliers are. It is expected that small vendors are more likely to be identified as having a higher level of risk in both datasets, because the simulation was designed to make small vendors with high-risk propensity were more actively involved in fraud.

Table 4 reports the percentage of vendors at different risk levels in both the empirical and simulated data. Vendors were categorized into four levels based on the risk indicators (from Level 0 to Level 3). For example, when a vendor meets the three risk indicators, the vendor is categorized as Level 3. In the state monitoring system, vendors at Levels 2 and 3 are considered to be high-risk. In the empirical data, approximately 5.3 percent of vendors were categorized as high-risk. In the simulated data, approximately 5.5 percent of vendors were categorized as high-risk. Therefore, this simulation also reasonably replicates the distribution of vendors by risk level in the empirical data.

Table 4: Percentage of vendors at different risk levels in the empirical versus simulated data

Risk level of vendors	Empirical data Percent	Simulated data Percent
Level 0	81.4	75.0
Level 1	13.3	19.5
Level 2	4.8	4.5
Level 3	0.5	1.0

Note: Level 2 and 3 are considered to be high-risk.

The distribution of vendors by risk level and store size is presented in Figure 4, and provides information on the outliers. Most vendors at Levels 2 and 3 were one or two checkout lane vendors in both datasets. Numbers in parentheses on the x-axis show the number of vendors that have such a number of checkout lanes in both datasets.

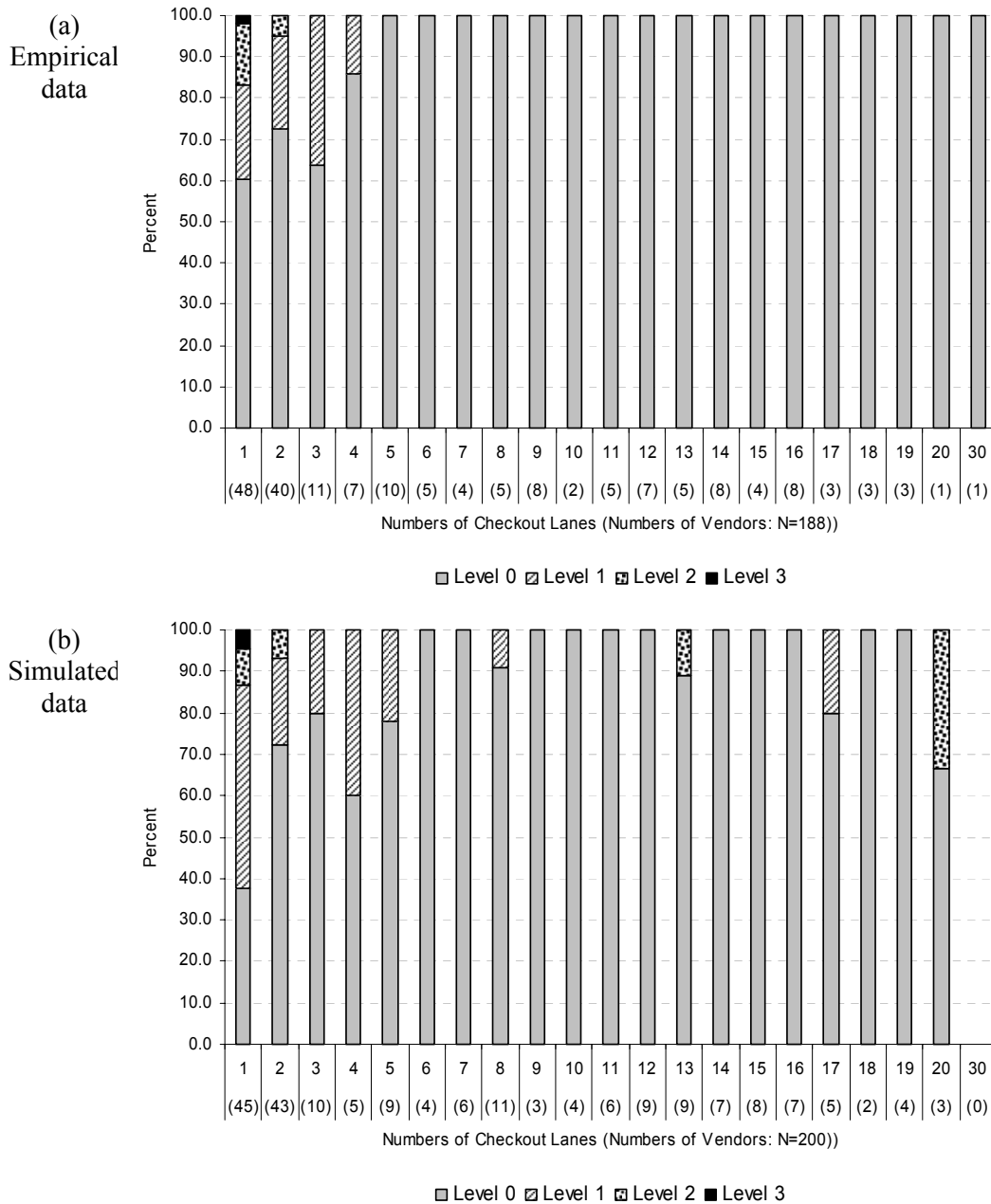
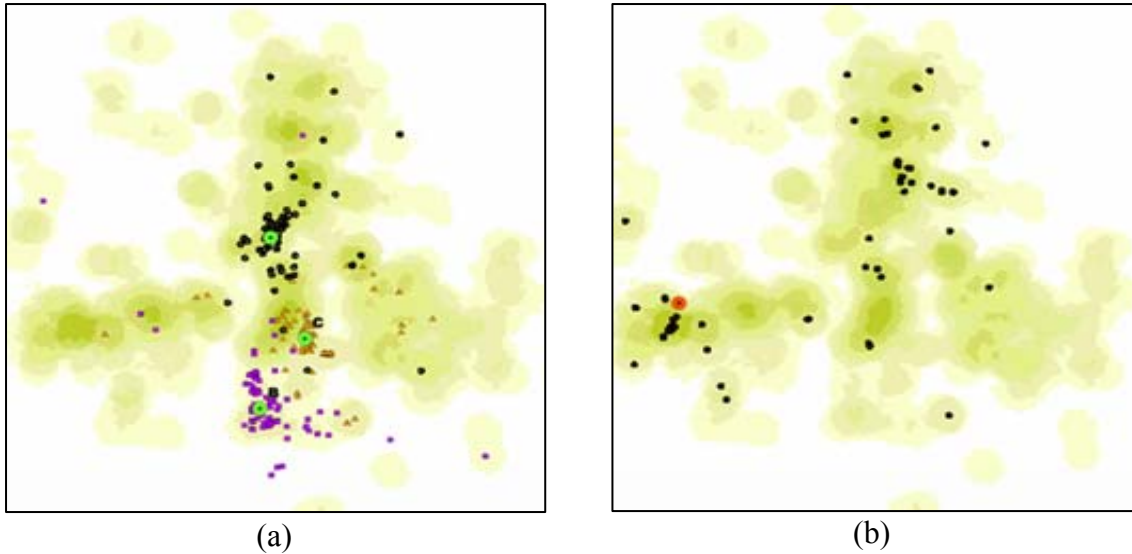


Figure 4: Vendor distribution by risk level and store size in the (a) empirical and (b) simulated data

Investigating Spatial Patterns

Along with the descriptive statistics, spatial patterns emerging from the interactions among vendors and participants were examined. In the retailing literature, for example, trading area patterns have been identified. A trading area contains the consumers of a particular firm or

groups of firms for specific goods and services (Berman & Evans, 1995). The trading area is broken down into three parts: primary, secondary, and fringe. According to this analysis, the majority of consumers (50 to 80 percent) come from the primary area, with an additional 15 to 25 percent of a store's customers in the secondary area. The remaining, most widely dispersed customers come from the fringe area. This implies that proximity to stores is an important criterion for consumer store choices. Store choice or spatial interaction models have conceived and extended this idea as a basic premise (Huff, 1964; Nakanishi & Cooper, 1974, 1982; McFadden, 1980). In Figure 5 (a) and (b), we present two maps that show spatial interaction patterns of normal and high-risk vendors in the empirical data.



Note: For illustrative purposes, large circles represent selected vendors. Small dots surrounding the vendors present participants who redeemed their benefits at the vendors. The background color represents the density of participants in the county. (a) presents a normal pattern in which the majority of the store's customers live close to the store; (b) presents the spatial pattern of a high-risk vendor, whose customer mainly come from areas far away from the store location.

Figure 5: Spatial interaction patterns among vendors and participants

To simulate the spatial pattern of vendors and their customers (i.e., WIC participants) using FraudSim, a hypothetical scenario was developed with 10 vendors and 2,000 participants. In the simulation, locations of the vendors and participants were randomly generated within a rectangular landscape. Dots represent participants, while squares represent vendors. Vendors and participants were randomly assigned risk propensities at the initialization. The numbers in decimals in the vendor box shows the randomly assigned vendor risk propensity. Each vendor was also randomly assigned to have one to twenty store checkout lanes which are presented in the second number inside each vendor box. The larger the square, the larger the number of checkout lanes.⁶

Figure 6 (a) shows the theoretical spatial pattern that can be expected when the Huff model is based on describing individual choice at the micro level. It is assumed that customers

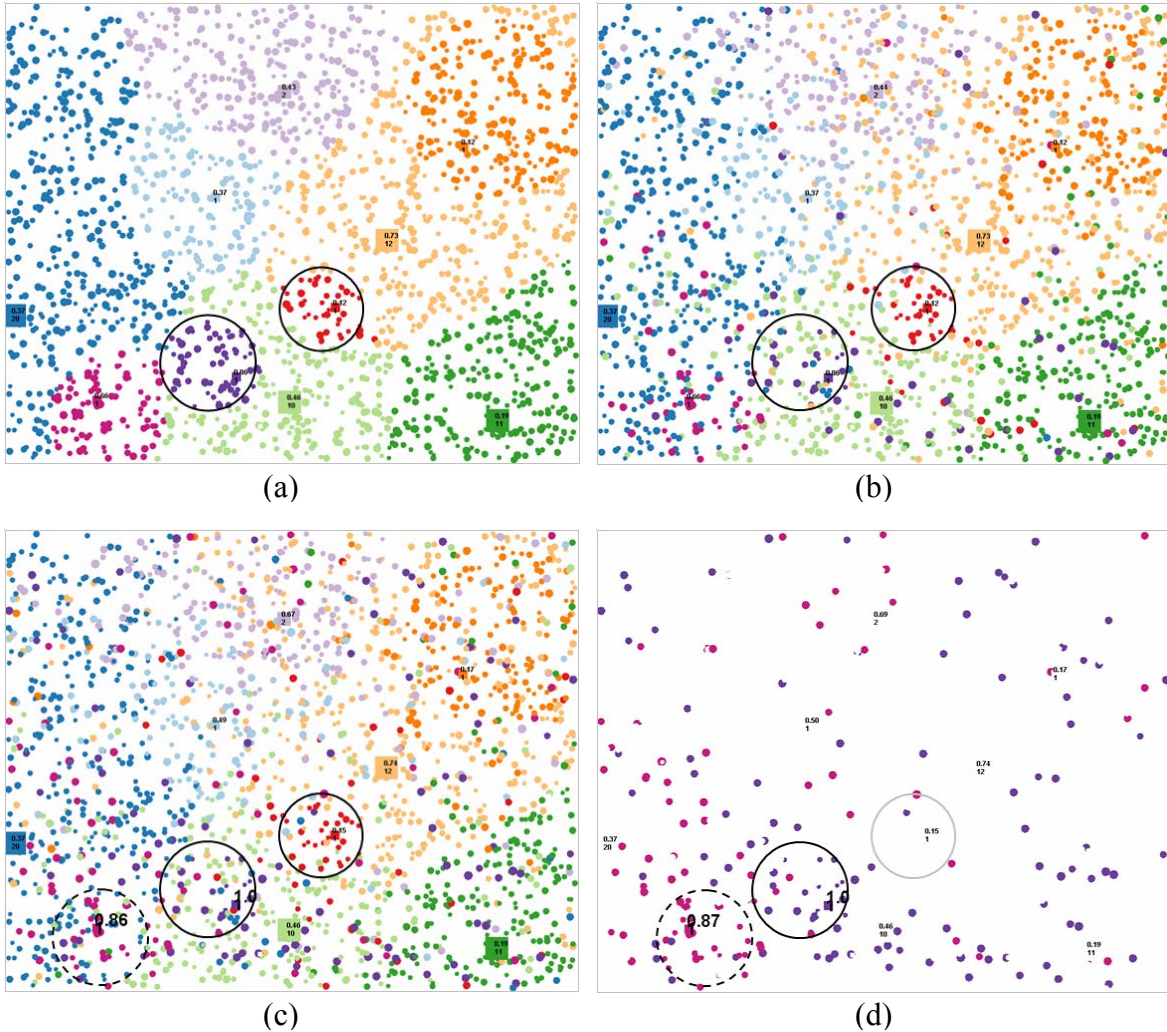
will choose stores based on economic rationality, and will maximize their utility based on certain deterministic factors. It is possible to incorporate other decision factors, such as store quality and availability of parking (summarized in Drezner & Eiselt, 2002), in order to generate different trading area patterns. However, the fundamental logic does not change.

In terms of a high-risk pattern, it is assumed that a vendor with high-risk propensity will lose participants with low risk propensity who are supposed to be served by the vendor, because negotiations to engage in fraud will most likely fail. Instead, these vendors will attract participants with a high risk propensity. These participants can be those who failed their negotiation with a vendor having low risk propensity at their initial choice. In other words, high-risk vendors lose those who are likely to visit the vendor and attract those who they are not likely to. This is ultimately reflected in the spatial patterns of vendors participating in fraud.

In Figure 6 (a), two small vendors were identified with relatively high (0.86) and low (0.12) risk propensities. Solid thick circles show the trading area of the vendors. Their interactions with the participant agents they were supposed to serve were watched. Figure 6 (b) shows the result of fraud negotiations at the initial stage. The vendor with high risk propensity failed to attract participants in the vendor's supposed trading area and started attracting participants who failed in negotiations with their theoretical vendors and were successful in negotiations with the high-risk vendor.

In Figure 6 (c), at Time 292, the vendor agent with high-risk propensity attracted more participants from hypothetical secondary and fringe areas, while other vendors kept their original patterns at Time 292. It was found that a small vendor next to the high-risk vendor was also developing as high-risk. However, the small vendor with a low risk propensity still maintained its original participants at Time 292. This simulation contrasts the different interactions between vendors and participants based on their risk propensities when the store size is the same.

Figure 6 (d) highlights the distribution of participants visiting the high-risk vendors at Time 308 by whiting out all other vendors from the landscape. The small high-risk vendor lost participants in the primary area and attracted participants from other areas who were not expected to visit from the current theoretical framework. Another developing high-risk vendor (inside dotted circle) also shows similar spatial interaction patterns. The high-risk vendor (inside solid circle) reached to the level of 1.0 (maximum risk propensity) from 0.86, while the low risk vendor remained at the level of 0.15, which is not different from the initial condition (0.12).



Note: (a) Theoretical vendor choices of participant when the Huff model was deterministically implemented at Time 0. Two small vendors were highlighted: one with relatively high risk propensity (0.86) and the other with relatively low risk propensity (0.12). (b) Fraud negotiations occurred at Time 1. (c) Fraud negotiations continue for those participants who have a relatively high risk propensity (> 0.6) and are not involved in fraud. While the small vendor with low risk propensity remained stable (risk propensity: 0.12 to 0.15), the high-risk vendor was actively attracting participants (risk propensity: 0.86 to 1.0) at Time 292. Another one-lane vendor next to the small high-risk vendor was developing as high-risk (risk propensity: 0.66 to 0.86) at Time 292. Other vendors were maintaining their original trading areas. (d) This highlights the interaction between small vendors with high risk propensity and participants at Time 308 (black solid and dotted circles). The small vendor with low propensity was faded out (gray solid circle) for the purpose of emphasis. All vendors are small, having one lane. The vendor's risk propensity inside the black solid circle was 0.86 at the beginning and quickly reached to 1.0 at the end of the simulation. The vendor was attracting participants from all areas.

Figure 6: Fraud Simulation

In sum, the interactions and interdependency among players in a public delivery system were modeled in our agent-based model, FraudSim, where routine activities of the agents in the policy system were specified. This simulation shows the development of some risky vendors when they opportunistically behave without appropriate guardianship. A possible mechanism underlying the patterns of fraud such as rational choice and fraud negotiation was explored. We assumed that most participants make rational store choice based on certain decision criteria in terms of selecting stores and fraud decisions are made based on their risk propensity and chance. This chapter shows that the agent-based model closely replicates the statistical and spatial patterns of fraud in the policy system at a certain point in time. Therefore, the model can serve as a framework for implementing different theoretical assumptions, modeling other underlying mechanisms, and testing policy options.

DISCUSSION

This chapter attempts to understand statistical and spatial patterns of fraud in the delivery of public services. Criminologists have intensively explored white collar crime since Sutherland. Research on white collar crime has often been focused on the significance of monetary loss or social class. Studies that examine dynamics of white collar crime within a spatial framework are relatively limited.

This chapter contributes to the body of literature in two different ways. First, we approached white collar crime using an agent-based model. Fraud in public delivery programs was framed as a complex system, and the underlying mechanisms of such fraud based on rational store choice and fraud negotiation were explored. This allowed us to replicate the distribution of vendors with risk status in the empirical data. Second, in Eck's words (1995), "to examine routine activity theory, simulations could be conducted to determine whether the crime patterns created match those observed in the real world." By comparing the results of the simulation with the observed patterns in the empirical data, we evaluated the legitimacy of the simulation model.

Policy implications can be drawn from this work. First, Kim (in press) identified unusual spatial interaction patterns between participants and vendors from the perspective of traditional store choice models. Her study shows that when fraud occurs in public delivery programs, spatial patterns are different from the prediction of consumer store choice models. The weakness of such approach is that we can only identify those who show abnormal patterns after committing fraud. When the process of developing vendors as high-risk can be understood, public agency may be able to discuss when and where they need to intervene to deter fraud. Second, the simulation can facilitate discussion of policy intervention among policy makers by incorporating their assumptions on the issue into the simulation. Agent-based modeling provides a flexible framework for this activity in practice.

Limitations

A major weakness of this study is that the agent-based model only captures the interaction between vendors and participants at the current stage. In practice, agents act in a more complicated fashion than what has been tested here. Participants can be involved in fraud among themselves, a group of vendors can be assembled to commit organized crimes, or an outside entity can be involved in the WIC business process. In this chapter, one of the main objectives

was to develop a foundation on which to build future studies by focusing on the most common fraud mechanisms.

While this simulation stepped forward in terms of introducing dynamics in the choice model, the actual WIC program is much more dynamic than the simulation. For example, in the agent-based model, vendor agents do not exit or get replaced; whereas in the WIC program, vendors are sometimes introduced or withdrawn. Voucher usage by participants was also simplified. Every voucher was used by participant agents each iteration. In reality, some participants may not use their vouchers at all during certain months. It was not tested how these characteristics will change the dynamic of fraud.

The simulation also has limitations in terms of decision-making. In the current simulation, participant and vendor agents make store choices and fraud decisions right away when they meet each other. In reality, both decisions may take longer and both parties may go through the process of trial and error. Other personal characteristics or situations may influence how decisions are made.

In addition to easy decision-making by agents, this simulation is built within the framework of a utility function. One advantage is that some of the well-established models and evidence can be applied in the simulation. A weakness, however, is that the simulation still holds limiting assumptions regarding human behavior. An example of this weakness appears when modeling the situation where a high-risk vendor is replaced by a new vendor. Once the replacement is made by the public agency agent, all participant agents recalculate their store choice probabilities without hesitation. In reality, it may take longer to inform participants and make them visit the new vendor which may alter the dynamics of fraud.

Agent-based models are developing as an alternative tool for studying complex natural and human phenomena. Compared to statistical or optimization procedures, the process of building and testing the models has not been firmly established. Several parts of our model are based on heuristics, rather than on parameters from empirical evidence. This aspect of the current models provides an opportunity, as well as a barrier, for extending this study.

Future Research Directions

When fraud in public delivery programs is approached from a management perspective, traditional criminology literature on criminality adds limited value to understanding the dynamic nature of crime in the real world. Focusing on the nature of criminals and calibrating the causes of crime do not tell us when, how, or why such criminal activities occur in public delivery programs. On the other hand, routine activity theory provides a framework to examine crime events as a convergence of offenders and targets in time and space. However, as Osgood, et al. (1996) suggested, there would not be sharp distinction between offenders and targets in this type of illegal and deviant behavior in the public delivery program. Fraud might be a side effect when players of the program opportunistically behave. This provides us an opportunity to examine the role of place managers or policy interventions in the system.

Crime is difficult to study because the process is not revealed in many cases. Traditional research methods and tools have limitations in studying such hidden processes and understanding the underlying mechanisms. Social simulation models have some promising aspects for studying issues of crime and public health. These models allow us to investigate interactions and interdependency, which is key to understanding the occurrence and diffusion of social issues.

Therefore, the applicability of simulation models is more relevant in areas such as crime and public health.

From a policy point of view, simulation models also have advantages, in that policy analysts can test the consequences of certain policy options into the whole system. A current approach to test the effect of policy interventions is to implement pilot studies. This approach has significant weaknesses and is more resource-intensive compared to social simulation techniques. Public managers cannot implement the same pilot project repeatedly for the same people while carefully observing consequences for a long time due to political and administrative constraints. Studying human subjects has ethical and confidential issues. If human and social systems can be studied using agents in a virtual laboratory, research and practice in the areas of policy and management can be improved.

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Notes

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- ² Given the nature and characteristics of vendors, participants, and employees in the program, the direct comparison of these numbers is not appropriate.
- ³ Data analysis was performed in May 2005 and was approved for publication without identifying the county and vendor names.
- ⁴ The total number of participants who redeemed their benefits was 28,887 in the month. However, participants usually visit more than a vendor to redeem their benefits each month. In April 2004, each participant visited approximately 1.5 vendors.
- ⁵ MASON stands for “Multi-Agent Simulation Of Neighborhoods... or Networks... or something...” <http://www.cs.gmu.edu/~eclab/projects/mason/>
- ⁶ The same size squares are used for vendors with more than 3 checkout lanes for presentation.