Destroying Creative Destruction: The social welfare cost of fraud *

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Abstract

This paper is the first, to our knowledge, to investigate the cost of financial reporting fraud to the real economy by considering how misinformation about competitors’ profits might lead a firm to make misguided decisions when it updates its strategy each period. We use an agent-based model to show that misinformation might significantly slow and/or inhibit firms’ ability to learn about consumer preferences and, in some higher fraud level cases, may actually cause firms’ production decisions to diverge from consumer preferences over time.

1 Introduction

Significant resources are spent throughout the world on financial statement fraud prevention and enforcement, yet relative to the resources invested, there is surprisingly little known about the value of fraud prevention. The dearth of research has been noted by some (Lev, 2003; Dunbar et al., 1995), and yet the lack of attention to the problem persists. The bulk of research on the costs of fraud have focused solely on its effects on shareholders, but fraud may have wider economic ramifications. Indeed, these collateral effects arguably turn out to be a more compelling justification of public policy intervention into financial reporting than that of shareholder protection.

This paper begins an investigation into one aspect of the potential wider economic effects of fraud. We look at how misreporting of success affects economic learning throughout the economy. To do this, we build an evolutionary agent-based model of a simple, single good economy where producers are attempting to discover consumers’ preferences for the good’s single variable attribute. We find that even small amounts of fraud inhibit producers’ ability to converge on even static and homogenous preferences, because competitors are unable to properly discern which producers are the most successful and therefore their strategy evolution is maladaptive.

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Our paper is in part inspired by the anecdote of AT&T’s experiences during the period in which WorldCom was committing fraud. AT&T’s CEO at the time was quoted by CNBC as saying “The market said what a marvelous management job WorldCom was doing and they would look over to AT&T and say, ‘these guys aren’t keeping up.’ So my shareholders were hurt. We laid off tens of thousands of employees in an accelerated fashion and I think the industry was hurt” (Faber, 2003). Furthermore, decision-making throughout the industry was distorted by the fraudulently reported broadband traffic numbers provided by WorldCom through their incorporation into government reports and standards and their repetition by influential industry watchers (Lynch, 2003). This anecdote is of such interest because it highlights the potential unexplored mechanisms by which financial statement fraud might translate into real economy effects: competitors factored information contained in the various fraudulent disclosures made by WorldCom’s executives into decisions ranging from labor levels to broadband infrastructure investment. In other words, financial statement fraud has the potential to distort economic learning and the growth, efficiency, and social welfare that results.

Our model helps build the case that ignoring secondary effects of fraud (and other forms of biased misinformation) is a serious oversight of the field. The potential effects of reporting fraud on economic learning are significant, sometimes counter-intuitive, and sensitive to the exact model specifications. This model serves as a baseline in building an understanding of how fraud and misinformation more generally interrupts or diverts economic learning.

2 Prior Research

While there is a literature that explores some of the costs of fraud and a more developed one that considers the role of learning in economics, this is the first paper, to our knowledge, that brings the two together to ask the question, what does fraud cost the real economy through (potentially) causing a slowed or misdirected learning process?

2.1 Social cost of fraud

The largest literature that addresses the question of social cost has concluded that the social welfare effect of financial statement fraud is close to zero, since for every shareholder that loses as a result of fraud there is a shareholder who gained an equal amount by being on the other side of the trade made during the period where the earnings of the company were misrepresented (Booth, 2005; Lev, 2003; Alexander, 1996; Langevoort, 1996; Arlen & Carney, 1992; Easterbrook & Fischel, 1985). Booth (2005) extends the argument to saying that the expected cost to individual investors is also zero, as long as the investor diversifies her portfolio.

This argument, however, takes a myopic view of the consequences of fraud. Some acknowledge that there may be additional costs beyond those imposed on the shareholders of the company.

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1We are not the only ones to have our interest piqued by this anecdote: Sadka (2006); Bagnoli & Watts (2008) also credit AT&T’s experience as a source of inspiration for their recent investigations.
in question, but dismiss those additional costs as negligible (Alexander, 1996; Langevoort, 1996; Easterbrook & Fischel, 1985). They do not support this assumption with any empirical evidence, however, and their logic appears flawed. As Becker (1968) demonstrated in his model of street property crimes, the social cost generally lies not in the transfer of wealth between property owner and criminal but in the defensive measures that property owners take to prevent the crime. Furthermore, in the case of financial statement fraud, the opportunity costs and destruction of information externalities are possibly significant sources of social welfare loss.

There has recently been other research into the possible broader economic effects of accounting information more generally and fraud specifically. Bushman & Smith (2001) call for research into the connection between accounting information and economic development, and Sadka (2004) develops a model of how information in financial statements allows competitors to learn from each other and improve efficiency in firm organization and production processes. If good information on competitors’ innovations improves social welfare through efficiency improvements, it stands to reason that misinformation on the effectiveness of strategies impedes efficiency improvements.

Sadka (2006) develops a model to demonstrate that indeed decisions made throughout the competitive product market can be affected by fraudulent reporting by one firm, since every firm will make different price and quantity decisions based on the exaggerated efficiency reported by their competitor. Bagnoli & Watts (2008) model a similar dynamic in a Cournot setting and find that firms have the incentive to manage earnings that relate to production costs in order to mislead competitors. While competitors are able to anticipate the direction of the bias, they do not fully incorporate it into their own pricing and quantity decisions. As a result, if the right conditions hold, the presence of earnings management in Cournot duopolies will result in under-production and over-pricing, relative to the full-information model. Durnev & Mangen (2007) find that competitor firms make inefficient investment decisions prior to a firm’s restatement announcement. Both Sadka (2006) and Kedia & Philippon (2007) develop the argument that the production decisions will be further distorted by the fraudulent firm because of the need to invest and produce at levels that support the reported performance, not the real performance, in order to make the fraud credible. Kedia & Philippon (2007) find that during periods of suspicious accounting, firms over-invest and over-hire and then shed the excess capacity when misreporting is discovered, thereby contributing to volatility in the factor and labor markets.

2.2 Economic learning

The role of learning in economic growth and technological change has long been a subject of interest. Prior research into the mechanisms of economic learning falls into two broad categories: within-firm learning, or learning-by-doing (Arrow, 1962; Fudenberg & Tirole, 1983; Stokey, 1988; Young, 1991); and between-firm learning, or technological diffusion (Wright, 1936; Griliches, 1957; Mansfield, 1968; Stoneman, 2001). Some research attempts to parse how both types of learning interact (Foster & Rosenzweig, 1995) or determine which type will be pursued under which circumstances (Jovanovic & Nyarko, 1996). While our model clearly emphasizes issues that arise in the spread of innovation
between firms, the issue of fraud raises fundamental questions about all forms of learning. For any firm trying to improve its standing in the market (or stay ahead of those behind it who are doing the same) it must first assess where its alternative choices stand in the spectrum of effectiveness or desirability. Fraudulent reporting has the potential to make the assessment fraught with opportunities to mis-order one’s options.

These forms of learning that explain the process by which new technologies are discovered and adopted feed into our understanding of macroeconomic growth. Neoclassical growth models assume an exogenously determined rate of technological change (Solow, 1956), but recognize that the rate of technological change is the primary determinant of the aggregate growth rate. As Solow (1994) acknowledges, this leaves the neoclassical model with a frustrating limitation in that it is silent about the determinants of technological change and therefore the policy levers that might lead to increased growth. The endogenous growth literature has developed to supplement the neoclassical model with an explanation for how such technological change might be endogenously determined (see, for example, Romer, 1986; Lucas, 1988; Romer, 1990). Of particular relevance is the paper by Aghion & Howitt (1992) that recognizes that a byproduct of technology creation is obsolescence: an important part of economic growth is retiring less productive processes and undesired goods so that their inputs can be put to better use.

This of course leads directly to Schumpeter’s notion of “creative destruction” as a critical part of economic development (Schumpeter, 1934). Schumpeter’s influence is also felt in a complementary line of research: that of evolutionary economics (Nelson & Winter, 1974, 1982, 2002; Nelson, 1995). This work uses evolutionary metaphors to explore the sorting process that goes on to select the new technology that takes over from the old. In an evolutionary paradigm, firms compete and evolve on a “fitness landscape,” one which may be as dynamic as the firms are themselves. Our model of firm strategy change is rooted in this evolutionary approach: rather than optimize over a complex and fully-understood set of possible strategies, our firms’ rationality is instead primitive and myopic in nature, responding to the apparent fitness landscape by applying a simple decision rule (“copy the best performer”).

All of the above described research comes to the unsurprising conclusion that technological development is critical to economic growth, and that learning plays an important role in technological development. Most of the research, however, assumes that the relative value of new technology is discernible. As this work demonstrates, if there is significant misreporting, that assumption may not hold, and that one explanation for differences in rates of technological change may be that in differences in the discernment rate, not in the generation of new ideas. Unlike a biological system, firms can choose to enter or exit or change their strategy, and that free will component to their response to the perceived fitness landscape can be materially affected by misreporting.

Complementary results to those in this paper can be found in research into the effects of temporal myopia on organizational learning (Rahmandad et al., 2009; Rahmandad, 2008; Gibson, 2000). In these cases, the misinformation comes from delays in observing the full value of an action or misinterpreting the source of success or failure when multiple periods of different strategies affect
the outcomes of a particular period. Here as well a firm can persistently select a suboptimal strategy. Though the source of the misinformation is not due to intentional distortions of competitors, the complexity of learning evolution under temporal myopia shares many similarities to the dynamics explored here.

3 Approach

As the WorldCom example shows, one potential consequence of financial reporting fraud is that it interferes with the process by which economic actors learn about the market in which they operate. Most economic analysis assumes that this information is either obvious or already known, but it is clear in any real business context that many players are operating with far less information. Our analysis approach is therefore selected to allow us to assume market participants have far less information about the nature of the market or the context they operate in than would allow for standard analytical tools to be applied.

To this end, we find that an heterogeneous agent-based computer simulation model is a useful way to explore the question and understand the dynamics involved. Agent-based modeling allows us to connect the micro-level decision process of heterogeneous uninformed agents operating in the context of fraud to the macro-level consequence of aggregate social welfare (Schelling, 1978). An agent-based simulation approach allows us to consider imperfect mixing, which results in heterogeneous, endogenously-derived local fitness environments (Ramandad & Sterman, 2008).

A big challenge with agent-based simulations in the era of cheap computing power is exercising restraint in the model design, so that any outcome can be traced back to the aspect of the model design that generated the observed behavior. One can easily code a model that is too complex to understand, making it difficult to parse model artifacts from genuine insights (Leombruni & Richiardi, 2005). Particularly as the dynamics we wish to explore have not been studied before, the model we develop here is designed to serve as a baseline against which more complex future research can be compared and with which we can develop some fundamental intuition about the nature of the problem. We therefore hew as closely as possible to other “baseline” models in both neoclassical and agent-based modeling traditions.

We model a market that, if it had perfect information, would be a traditional competitive product market with homogeneous consumer preferences and a uniform production process. The only variations we make are: 1) to impose a rudimentary local information structure and; 2) to add some fraudulent agents to the system. A local information structure enables us to compare both fraudulent and non-fraudulent areas of the firm landscape at the same time and allows any effects of fraudulent activities to take shape without the strong dampening of a fully connected information structure. Further, we assume that our firms do not know that they are operating in such a simple market. Instead, firms know nothing about the nature of consumer preferences or of the overall size of their potential demand, and they must search along one variable dimension (a variable that does not change production costs) to discover an attribute that will appeal consistently to consumers. By adopting most of the elements of a competitive market we are able to abstract away from price...
competition and other strategic considerations. This choice allows us to establish clear causal links between fraudulent reporting and changes in welfare.

Fraudulent reporting creates a specific type of distortion to the learning process or competitors. When our firms have the simple updating heuristic to “copy the best performer,” no frauds that do not change the perception of who is the best performer are relevant to the model, and therefore are excluded from this examination. Instead, we examine only fraud that results in a perturbation to the true ranking of competitor firms in a neighborhood. This allows us to use a crude implementation of fraud—our fraudsters always report the maximum possible earnings—without loss of generality.

The significant simplifying assumption comes in considering how to model firms’ response to fraud. Here, we take our cue from previous agent-based modeling work: we assume zero-intelligence in our firms when it comes to discerning or responding to deception. Gode & Sunder (1993) demonstrate that a double auction trading institution can generate close-to-efficient prices even when traders are zero-intelligence traders. In a similar vein, we demonstrate that firms using a rote-learning heuristic, with no memory or skepticism, can reach the same equilibrium as would be employed by fully-informed, rational firms after a trivially-short learning process when the market produces non-fraudulent information. By adopting the zero-intelligence assumption, therefore, our fraud-free baseline still returns the traditional competitive product market results while the updating process offers a reasonable baseline against which more complicated updating strategies can be compared. This “zero-intelligence” approach can also be justified as a reasonable proxy for the inability of a firm with fully rational faculties but no information about the parameters of the competitive landscape to draw meaningful inferences about the outcomes they observe.

4 Model

We present here a model that reduces to as few dimensions as possible an economy that interacts fraudulent reporting with learning. Our model looks at firms whose only challenge is to decide whether to change their strategy in order to maximize revenues in the next period. Our questions are: is this kind of learning corrupted by fraudulent behavior (as in notorious examples in real life)? Does fraud decrease consumer welfare? If welfare is found to decrease under fraud, then what kinds of fraudulent behaviors are most harmful?

4.1 Overview

Our economy has consumers with homogeneous and stationary preferences and firms with identical production technologies and costs. There is one good produced in the economy, and this good has only one variable dimension that can be described as an ‘attribute’ which corresponds to a value, [0, 1]. Every consumer purchases exactly one unit of the good in each time period. The only decisions that occur in each period are: each firm must decide what value of the attribute of their good to produce that period and each consumer must decide where to purchase that period’s good. Firms wish to maximize profits, and consumers their utility. The only issue the economy must
resolve through learning is that firms do not know what value of the attribute consumers prefer. Instead, they must discover that value through a combination of trial and error and learning from the successes of their competitors. Furthermore, we consider an economy that is limited in its geographic horizons. Consumers are limited to purchasing their good from a local firm, and firms only learn about the activities of their immediate neighbors.

Throughout our model, after firms have each chosen the attribute they will produce that period, consumers purchase that period’s good from the firm in their neighborhood that sells the good that is closest to the preferred attribute. Consumers always make this selection without error and are unconcerned with where they purchased from in previous periods. Fraudulent behavior by firms likewise does not influence consumer decisions. Of course, each purchase transfers revenue to the firm producing the preferred good, and is the sole medium of information transmission from consumer to producer. Firms then have the opportunity to share their private information about consumer preferences through their required financial reports at the end of the period. However, there is the potential for firms to overstate their earnings if they decide to submit fraudulent reports.\(^2\)

We introduce the instances of reporting fraud in two ways: stochastically and endogenously. We allow in all experiments for the possibility that some portion of the firms in our economy never commit fraud. But of those that have the capacity to commit fraud, they will do so only in some instances. In the stochastic fraud scenario, their decision to misreport their profits is orthogonal to their performance and is therefore modeled such that each potentially fraudulent firm will commit fraud with some exogenously set probability. In the endogenous fraud case, firms with the potential to commit fraud will only do so with some probability if their real profits fall below a threshold that triggers their propensity for fraud. As in the stochastic case, even if the firm’s profits fall below the threshold needed to trigger the propensity to commit fraud, firms will do so only with some exogenously set probability.

After all of the firms report their period’s earnings, each firm must decide what attribute to produce in the next period. For all firms, fraudulent or not, each firm compares the firm with the highest reported earnings in their neighborhood with their own earnings. If the firm is not the highest earner in its neighborhood, it changes its attribute strategy in the next period to mimic the strategy of the best performing local firm (which is public information). To incorporate a crude proxy for skepticism and/or the costs of changing strategy, rather than have firms adopt the target strategy completely, they take the weighted average of their current and target strategies. In addition, there is a small error term ($\epsilon$) added to every move in strategy. For the fraudulent firms’ updating, we test two different scenarios: first, where the fraudulent firm “covers up” its fraud by making its update on the basis of its fraudulently reported income and, second, where the fraudulent firm is not concerned about ensuring its updating matches its reported earnings. In this scenario, the fraudulent firms compare their true earnings to the reported earnings of their local

\(^2\)In the real economy, firms will sometimes fraudulently understate their earnings. We do not model that behavior here.
competitors and update accordingly.

These two sets of two scenarios means that our simulation experiments fall into a 2x2 matrix:

<table>
<thead>
<tr>
<th></th>
<th>Change</th>
<th>Cover-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stochastic</td>
<td>Stochastic-Change</td>
<td>Stochastic-Cover-up</td>
</tr>
<tr>
<td>Endogenous</td>
<td>Endogenous-Change</td>
<td>Endogenous-Cover-up</td>
</tr>
</tbody>
</table>

Within each of these four experiments, we run simulations that search the different combinations of the fraction of the firms who might ever commit fraud and the probability with which they will commit fraud once any conditions necessary to commit fraud are met.

4.2 Details

The model described above is detailed as follows, and the timing of the model is summarized in Algorithm 1 below.

We consider a static population of agents $N$ which is comprised of two non-intersecting subsets: consumers $C$ and firms $F$; having representative individuals $i$ and $j$ respectively (i.e. $N = C \cup F$). While consumers are considered to be homogeneous, firms are not. Firms come in one of two varieties, either honest or dishonest. Whereas honest firms never enter into fraudulent behavior, dishonest firms can behave fraudulently, though they will not always do so. We record honest and dishonest firms by setting the register $s_j = 0$ and $s_j = 1$ respectively. We control the fraction of firms who are dishonest by the parameter $\alpha$.

In what follows, we assume that the cardinality of each set is $n$ ($|C| = |F| = n$), such that the total number of agents (consumers and firms) $|N| = 2n$. We assume that all agents are uniformly dispersed on a square lattice of side-length $l$ with continuous boundary conditions (i.e. a torus) such that each lattice site is occupied by exactly one firm and one consumer. Define by $N^i$ and $N^j$ the neighborhood of a representative consumer and firm respectively. For simplicity, we assume that each neighborhood is defined in an analogous way, being the Moore neighborhood surrounding the agent.\(^3\) By convention, let $i \in N^i$ and $j \in N^j$. When we discuss the Moore neighborhood of $i$ or $j$ exclusive of $i$ or $j$, respectively, let $N^{-i} = N^i \setminus \{i\}$ and $N^{-j} = N^j \setminus \{j\}$.

Next, define by $a^x \in [0,1]$, $x = \{c,f\}$ be the current attribute of the good that is preferred by

\(^3\)A Moore neighborhood contains the eight cells immediately adjacent to the agent as well as its own cell for neighborhood sizes of nine.
Algorithm 1 Main loop with conditional components for each Scenario

1: **Initialise Model**
   \[ a_i^c \leftarrow \bar{a} \quad \forall i \in C \]  // Assign uniform consumer preference for attribute
2: \[ a_j^f \leftarrow \text{rand} \quad \forall j \in F \]  // Randomly assign initial firm productions of attribute
3: **for all** \( j \in F \) **do**
4:   \( \text{if} \ \text{rand} < \alpha \) **then**
5:     \( s_j \leftarrow 1 \)  // Set some firms as potential fraudsters
6:   **else**
7:     \( s_j \leftarrow 0 \)  // Others always honest
8: **end for**
9: **The main loop**
10: **while** \( t < T \) **do**
11:   \( m_i \leftarrow \{ j : \text{argmax}_j u^i(j) \quad \forall j \in N^i \} \quad \forall i \in C \)  // Consumers find best firms
12:   \( \pi_j^a \leftarrow \#\{ i : m_i = j \quad \forall i \in N^j \} \quad \forall j \in F \)  // Firms receive profits due to local customer base
13: **for all** \( j \in F \) **s.t.** \( s_j = 0 \) **do**
14:   \( \pi_j^r \leftarrow \pi_j^a \)  // Report honestly
15: **for all** \( j \in F \) **s.t.** \( s_j = 1 \) **do**
16:   **if** \{ **Scenario: Stochastic & (rand < \beta)** \} \text{OR} \{ **Scenario: Endogenous & (rand < \beta) & (\pi_j^a \leq \bar{\pi})** \} **then**
17:     \( \pi_j^r \leftarrow \pi^* \)  // Commit fraud
18:   **else**
19:     \( \pi_j^r \leftarrow \pi_j^a \)  // Report honestly
20: **end for**
21: **Select and set target attribute for each firm**
22: **for all** \( j \in F \) **do**
23:   **if** **Scenario: Change** **then**
24:     \( \tilde{a}_j^f \leftarrow \{ a_j^f : \pi_j = \max(\pi_{N-j}^r, \pi_j^a) \} \)
25:   **else if** **Scenario: Cover** **then**
26:     \( \tilde{a}_j^f \leftarrow \{ a_j^f : \pi_j = \max(\pi_{N-j}^r) \} \)
27:     \( a_j^f \leftarrow \lambda \tilde{a}_j^f + (1-\lambda) a_j^f \)  // Set new firm attribute
28: **end if**
29: **end for**
30: **end for**
31: **end while**
32: **end for**
33: **end for**
a consumer or is produced by a firm. For this baseline model, we shall assume that all consumers prefer exactly the same attribute setting, while firms initially produce a good with an attribute drawn from the uniform distribution on $[0, 1]$.

In the course of the model, consumers will choose firms to frequent by applying a utility criterion, while firms gain profit by attracting customers. Profits are equivalent to revenue earned in this model, since we normalize the homogeneous production costs to zero. We choose the simplest form of utility function given a consumer $i$ and firm $j$ based on the distance between attributes,

$$ u^i(j) = 1 - \text{abs}(a^i_c - a^j_f). $$  

At the beginning of a period, consumers will consider $u^i(j)$ $\forall j \in N$ and choose to patronize exactly one firm $j^*$ in their neighborhood which gives them the maximum utility (splitting ties equiprobably), setting their firm choice variable $m_i = j^*$. After consumers have made their decisions, firms gain profits due to the patronage of consumers from the neighborhood. We call this profit the firm’s actual profit and define a rudimentary profit function as follows,

$$ \pi^a_j = \#\{i : m_i = j \forall i \in N^j\}. $$  

This completes the interaction phase of a stage. At this point, the model diverges depending on which of the four scenarios is operational.

4.2.1 Stochastic change

In the reporting phase not all firms are honest. Firms who are of dishonest type ($s_j = 1$), in the first instance, commit fraud each period with probability $\beta$. For this reason, we label this model ‘stochastic fraud’. We interpret fraudulent behavior to be when a firm, irrespective of their actual profit $\pi^a_j$ decides to report the maximum possible profit $\pi^* = |N^j|$. Hence, fraudulent behavior distorts the profit signal such that other firms (whether dishonest or not) may unwittingly imitate the attribute of an under-performing firm in their neighborhood.

In the final, learning phase of the model, firms have the option to costlessly revise their attribute setting. Firms are assumed to have access to both the attribute decisions and reported profits of firms in their neighborhood set. Each firm (regardless of its fraudster status) compares its actual revenues with the reported revenues, $\pi^{r,N_{j-}}$, of its best-performing neighborhood firms and chooses a target attribute $\tilde{a}^f_j$ to modify its strategy towards, i.e. $\{\tilde{a}^f_j : \pi_j = \max(\pi^{r,N_{j-}}, \pi^a_j)\}$. If $\pi^a_j < \pi^{r,N_{j-}}$, the firm adjusts its next-period attribute in the direction of attribute of the highest-performing firm by taking a weighted average of its current attribute and its target attribute, where the weight placed on the target attribute is $\lambda \in [0, 1]$. Finally, so that firms don’t get caught prematurely in a suboptimal portion of the fitness landscape, we assume firms update with a slight error, $\epsilon$, drawn from a uniform distribution on $[-0.01, 0.01]$. 

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4.2.2 Stochastic cover-up

The stochastic cover-up model proceeds through the reporting phase in an identical manner to the stochastic change model. The learning phase, however, is slightly different. In this case, the target attribute is selected comparing all of a firm’s neighborhood’s reported profits, ignoring its own actual profits: \( \tilde{a}_f^j : \pi^r_j = \max(\pi^r_{N(j)}) \). Effectively, this means that fraudsters covering-up their fraud will repeat their current strategy in the next period. This follows from the fact that they will, at minimum, tie for highest reported earnings, thereby triggering the decision rule to remain with one’s own strategy in the case of a tie.

4.2.3 Endogenous change

The endogenous change model is identical to the stochastic change model except in the reporting phase. Rather than simply report \( \pi^* \), those firms where \( s_j = 1 \) will report \( \pi^* \) with probability \( \beta \) when \( \pi^a_j \leq \bar{\pi} \) and rand < \( \beta \).

4.2.4 Endogenous cover-up

The endogenous cover-up model combines the reporting phase of the endogenous change model and the learning phase of the stochastic cover-up model.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Explanation</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>Fraction of firms who are potentially fraudulent by nature (i.e. who have ( s_j = 1 ))</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( \beta )</td>
<td>Probability that a firm (with ( s_j = 1 )) will commit fraud</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( \bar{a}^c )</td>
<td>Consumers’ preferred attribute level</td>
<td>0.32</td>
</tr>
<tr>
<td>( a^f_j )</td>
<td>Actual attribute produced by firm ( j )</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( \tilde{a}^f_j )</td>
<td>Target attribute selected by firm ( j ) to update next period’s attribute strategy</td>
<td>([0,1])</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>Weight placed on target attribute</td>
<td>0.5</td>
</tr>
<tr>
<td>( \bar{\pi} )</td>
<td>Critical profit level in Endogenous fraud scenario that causes a fraudulent firm with actual profit equal to or less than ( \bar{\pi} ) to consider fraud</td>
<td>0</td>
</tr>
<tr>
<td>( \epsilon )</td>
<td>Slight variation in learning of a best-performing neighbor’s attribute level by which a firm will offset their attribute setting</td>
<td>([-0.01, 0.01])</td>
</tr>
</tbody>
</table>

Table 1: Summary of model control parameters
4.3 Experimental plan

We explored the consequences of each of the four models by incorporating their algorithms into simulations performed by NetLogo. We selected 62 pairs of values for $(\alpha, \beta)$, which correspond to the fraction of the population capable of committing fraud and the probability with which they commit fraud, respectively. For each pair we ran the simulation for 1000 time-steps with 50 different sets of initial conditions. Throughout, we have arbitrarily set the consumers’ preferred attribute to 0.32, which has the advantage of being neither close to a boundary nor dividing the possible attributes symmetrically.

The pairs of values for $(\alpha, \beta)$ were chosen to systematically search the space, paying particular attention to the areas with either very low rates of fraud or very high rates of fraud. To that end, we selected pairs whose product (corresponding to expected fraud in each period in the stochastic cases) were equal to the following set:

$$\alpha \cdot \beta \in \{0, 0.01, 0.03, 0.05, 0.1, 0.2, 0.4, 0.6, 0.8, 0.9, 0.95, 0.97, 0.99, 1\}$$

We also wanted to be able to see whether the composition of the overall fraud rate matters—in other words, we were interested in whether the effects are driven by the expected fraud or the values of either $\alpha$ or $\beta$ separately. The pairs were therefore selected that simultaneously solved for the desired product and one of:

- $\beta = 1$
- $\beta = \frac{1}{2} + \frac{1}{2} \alpha$
- $\beta = \alpha$
- $\beta = 2\alpha - 1$
- $\beta = \alpha\beta$

To reduce computation time, only one pair each that results in zero fraud or 100% fraud was used in each experiment. As it turns out, there seem to be interesting tipping points occurring somewhere between expected fraud levels of 0.2 and 0.4. Therefore, after our main simulation runs, we went back and more thoroughly searched the parameter space in that region, using the same functions to generate pairs of $\alpha$ and $\beta$ that resulted in the following set:

$$\alpha \cdot \beta \in \{0.22, 0.25, 0.28, 0.31, 0.34, 0.37\}.$$ 

This resulted in 4600 trials for each of the four experiments or 18400 trials in all. Figure 1 shows the complete set of pairs selected.

Because the NetLogo built-in facility for running large numbers of experiments is not well-designed for the pair design we chose (it requires every desired $\alpha$ to be paired with every desired $\beta$), we used the NetLogo-Mathematica Link add-on that allows Mathematica to run the experiments
Figure 1: Values for $(\alpha, \beta)$ tested in each of the four experiments

and collect the resulting data. We collected the actual fraud rates, $\frac{1}{|F|} \sum_j s_j$, and the population mean utility level, $\frac{1}{|C|} \sum_i u^i(m_i)$, for each timestep.\(^4\)

Figure 2 shows a screen shot of a simulation in progress. In this instance, $\alpha$ is set to .35 and $\beta = .8$, and the simulation is running an endogenous-change experiment.

4.4 Measures of social welfare

By eliminating income, price, and variable demand from our model, we have the benefit of concentrating all of the variation in overall economic wellbeing into one metric, consumer utility. While individual firms will do better and worse, the aggregate number of sales is fixed in each period, so firm revenues will not change social welfare. The disadvantage of this approach is that utility lacks a concrete scale—even the idea of aggregating utility directly is problematic (Arrow, 1951)—and therefore we are limited in our ability to speak in absolute terms about the types of costs to society of fraud explored here. The utility numbers convey no notion of the importance of relative changes in utility, since it would be reasonable to consider that the good modeled here is not the only source of consumer utility. Therefore, the policy relevance of a particular magnitude of utility losses will depend entirely on the specific application one chooses for this model.

The model design confines feasible utility ranges from 0.32 to 1, where a consumer will have a

\(^4\)Additional variables were collected that are beyond the scope of the analysis discussed here. These data are available from the authors upon request.
utility of 0.32 only if all of the producers in her neighborhood are making goods with the attribute 1, the attribute which is the furthest possible from her preference for 0.32. Consumers would reach the maximum utility in a perfect world if for every consumer there is at least one firm in their neighborhood producing at exactly 0.32. In practice, this will not ever quite be reached due to the mutation term that is introduced when firms change strategies. Another focal point of consumers’ utility is the expected level of utility if firms produce randomly: that is, the expected value of the maximum $1 - \left| a^c_i - a^f_j \right|$ of nine random draws of $a^f_j$, which, when $a^c_i = 0.32$, is 0.949998.

We elect, therefore, to map the raw utility measures generated by our simulation onto a scale that helps relate the experiences of a particular simulation run to that of a fraud-free economy. To this end, we set the expected utility at the start of the simulation (in raw utility terms, 0.949998) to zero and the average, long run fraud-free utility to one. That long run, fraud-free utility level is calculated by taking the average of the last 100 time steps of each of the 200 fraud-free runs tested across the four experiments, which in raw values is 0.999958. Hereafter, therefore, all of the utility measures reported will be the raw utility measure transformed by the equation

$$U^i = 20.016 \cdot u^i - 19.015$$

which means that consumers’ per-period utility is defined over the domain

$$U^i \in \{-12.61, 1.001\},$$

and that utility levels between zero and one also convey the percent of the total normal utility gain from a zero information environment to the equilibrium fraud-free environment.

Another challenge in developing an appropriate measure of the social welfare costs of fraud is the question of how to weight utility changes over time. As will be discussed below, consumers’
utility time series have quite complex dynamics, and the direction and magnitude of change from
one time step to the next can change more than once, depending on the level of fraud. Therefore,
choices of which part of the time series one chooses to focus on can have a significant effect on how
one interprets the results.

If the financial reporting modeled here represents, say, quarterly reporting, then the time span
of our simulations is 250 years. For those simulations that appear to be finally converging on the
fraud-free levels of utility towards the end of the simulation run, that would be cold comfort indeed.
On the other hand, there are clearly initial condition effects in early steps of the model that are
perhaps less relevant to real life and what we should be more concerned about are equilibrium level
differences in states across levels of fraud.

One obvious way to balance the question of timing is through calculating the discounted present
value of the utility stream in each trial. It provides a useful, one-dimensional initial impression of our
data, and we will present these results first below. However, there are two sources of complications
in constructing the present value numbers: the results are sensitive to the choice of discount rate,
and the results need to control for variation in the initial conditions.

We present the data using an annual discount rate of seven percent, following OMB guidelines
(Office of Management and Budget, 1992), and we consider each time step to be a quarterly report.
To calculate the discounted present value of the utility stream in each run, therefore, we use the
following equation:

$$\sum_{t=1}^{1000} \frac{U^i_t}{(1 + 0.068/4)^t}.$$ 

We cannot use the mean present value of each \((\alpha, \beta)\) pair as a reliable summary statistic of that
area of the parameter sweep, however. There is a strong relationship in many of the pairs between
the initial conditions, as measured by the first period utility, and the discounted value of the utility
stream. (This is unsurprising, given that the discounting process puts heavy weight on the first
period’s utility.) Since there is some variance in the distribution of initial conditions from trial to
trial, this makes direct comparisons of means invalid. In other words, while the expected utility
in period one is zero, the actual utility in that period is distributed around zero. Even with 50
runs per parameter pair, there is enough variation in the means of the first periods to make direct
comparisons between parameter pairs misleading. To correct for this, we regress the discounted
value of the utility stream against the first period utility for all of the runs within a trial. We then
report the intercept term from the regression—in other words, the expected discounted value when
the initial utility is equal to its expected value, zero.

5 Results

The results of our four experiments have produced intriguing data, much of which is counter-
intuitive. Together, they make the case that fraud’s effects on economic learning could be significant
and are worthy of considerably more research than can be done in the scope of this paper.

5.1 Analysis of a fraud-free environment

The average consumer utility in the fraud free model quickly converges to one. In the fraud free economy, in all of the 200 runs the average consumer utility exceeded 0.95 by the sixth step, and by the tenth time step, all of the runs had reached an average utility of at least 0.99. In those initial steps, the consumer tension is approximately halved in each time period. This relationship fades out when the effect of the \( \epsilon \) mutation term begins to dominate the learning effect.

Figure 3 shows the average utility changes in the first 20 time steps for each of the 200 fraud-free runs conducted across all four experiments. As can be seen in this figure, initial condition differences are quickly erased, and in a fraud-free economy, producers uniformly and predictably discover consumers’ preferences. Over the full run there continue to be slight perturbations to consumer utility levels, but these changes are small: the standard deviation of the utilities in each time step across all runs is less than 0.001 after the tenth time step. The mean discounted present value of the utility stream of a fraud free economy, conditional on an initial utility of zero, is 56.76, with a 95% confidence interval of (56.75, 56.77).

Economies with even the lowest levels of fraud perform consistently worse. The differences in mean utility levels for economies with minimal levels of fraud are small (much less than half a percent on average) but they are statistically significant at the 99% confidence level beginning no later than the fourth time step. The present value statistics for the lowest levels of fraud are similarly statistically significantly lower than the present value of a fraud-free economy.

5.2 Social welfare effects of fraud

Immediately upon inspection of our data, it was clear that misreporting interferes in the ability of an economy to discern consumer preferences. At the lowest levels of fraud, the effects are comparatively modest, but the utility costs climb quickly as fraud increases beyond the lowest levels. The consequences of the fraud are also quite sensitive to the model specification: stochastic versus endogenous have significantly different effects, as do the fraudster strategies of changing or covering-up. Furthermore, there are distinct differences among trials with the same overall levels of fraud due to the contributions of \( \alpha \) or \( \beta \) to that level. And in some cases, the initial conditions continue to exert effects throughout the run of the model, creating widely divergent outcomes between different runs with the same parameter settings.

5.2.1 Overview of results

While they suppress much detail, the expected present value of the utility streams of each trial provide a succinct overview of our results. Figure 4 reports in the five lines for each plot, the present value of the utility streams as a function of \( \alpha \cdot \beta \), where each line conveys the results for

\[5\] The speed with which the economy converges on the correct attribute is a function of the \( \lambda \) term.
Figure 3: The average consumer tension in the first 20 time steps of each of a random sample of 20 runs (from 200) of a fraud-free economy.
a different \( \beta \) as a function of \( \alpha \). In all cases, all results fall statistically significantly below the expected present value of the fraud-free utility streams.

Several results are immediately apparent. First, while in general within experiments, utility declines as fraud increases, this is not true in all cases. Holding the relationship between \( \alpha \) and \( \beta \) constant, the stochastic cover-up experiment offers the clearest case of instances where higher fraud rates perform unequivocally better than do lower fraud rates. Looking across the different relationships between \( \alpha \) and \( \beta \), we see routinely in all four experiments examples where higher rates of fraud perform better than lower rates.

Second, both stochastic experiment results are entirely non-negative, meaning that, in all cases, the net present value of the utility stream is no worse than would be the case if firms never updated their production strategy. This is not the case for the endogenous fraud experiments: here, the present value of utility is negative beginning at relatively low levels of \( \alpha \cdot \beta \) (between 0.15 and 0.35). Similarly, the two experiments with cover-up updating strategies tend to perform worse than the changing strategy with the same fraud generating process. The differences are particularly stark in the endogenous experiments: at the higher fraud rates, the cover-up experiment performs approximately twice as badly as does the change experiment. The stochastic cases also have significant regions where the cover-up present value is half that of the change experiment with the same parameter values, though the differences in performance are much smaller in absolute terms.

Finally, there are clear differences in utility levels for a given \( \alpha \cdot \beta \) depending on relative values of \( \alpha \) and \( \beta \). In general, the cases where \( \beta = 1 \), when the same firms commit fraud in every period, the present value of consumer utility is worse than other combinations of \( \alpha \) and \( \beta \), and when all firms have the capacity to commit fraud (i.e. when \( \alpha = 1 \)) consumers do better. The notable exception to this is in the stochastic cover-up experiment where the present value of utility levels off for the cases where \( \beta = 1 \) at \( \alpha \cdot \beta = 0.25 \) and remains more or less constant all the way to \( \alpha \cdot \beta = 0.8 \) while the other combinations of \( \alpha \) and \( \beta \) continue to fall.

One consequence of these results is that there exist regions of the parameter space where similar rates of fraud can result in dramatically different outcomes, depending on exactly how that fraud is generated and how fraudsters update their strategies. One clear example of this is when the rate of fraud is approximately 20 percent. (Note that the real fraud rates are different—and lower—than the \( \alpha \cdot \beta \) measure, an issue discussed further below.) The net present value of the utility stream of an economy with a fraud rate of approximately 20 percent can range from almost 50—nearly 88% of the utility gained from a fraud-free economy—to \(-48\), a similar magnitude loss in utility from the random strategy selection baseline. The best of all worlds comes from the stochastic change experiment when \( \alpha = 1 \) and \( \beta = 0.22 \). The worst is in the endogenous cover-up experiment when \( \alpha = 0.25 \) and \( \beta = 1 \).

5.2.2 Analysis

Intuitively, one might expect fraud to interfere with learning in relatively predictable ways: as fraud increases learning slows, and, perhaps, at the highest levels, learning is essentially blocked.
$\alpha \cdot \beta$

Figure 4: Present value of consumer utility streams (discounted at 7%) for the four experiments. Note the changes in scale for the y-axis.
It turns out, however, that intuition is not a particularly helpful guide to understanding the model results. In particular, in every dimension of our simulations, our results display a high degree of non-monotonicity: functions relating any two of the three relevant dimensions of time, real fraud rate, and consumer utility are non-monotonic over significant portions of the parameter sweeps. The present value results already displayed in Figure 4 demonstrate that non-monotonicity in the relationship between fraud rates and utility. Figure 5 shows an example from each experiment where the function between time and utility is non-monotonic. The pictures shown in Figure 5 are all from the same point in the parameter sweep, to allow for more direct comparisons across experiments, but in general, the non-monotonic timeseries behavior occurred most clearly in different areas of the parameters, depending upon the experiment. None had this behavior at low levels of fraud \((\alpha \cdot \beta \leq 0.05)\) but all had at least some non-monotonic timeseries at higher levels.

Understanding the reasons behind this persistent non-monotonicity helps illuminate further the effects of fraud on learning. Our hypothesis for why the simulations show such non-monotonicity rests on the interacting dynamics of firms’ strategy change behavior. We have identified several factors that contribute to this behavior.
At root, utility will improve if more firms produce goods close to consumer’s preference. Likewise, utility will decline if an increasing number of firms produce goods with undesirable attributes. In a fraud-free environment, the top performing firms exert an un-interfered pull on their competitors, which results in continuous utility improvements (with the minor exception of the role the error term plays in very small strategy shifts). Once fraud is introduced, that pull has to compete with the noise created by the fraudsters. Fraudsters will decrease consumer utility only to the extent they are producing less desirable attributes than their neighbors.

Utility will increase under four scenarios, therefore:

1. In fraud free neighborhoods;

2. When the fraudster himself is selecting more desirable attributes than his neighbors;

3. When a high-performing firm can compete in attraction with the fraudster firms; or

4. When a firm currently producing on one side of the consumer preference (i.e. 0.32) chooses a target attribute that happens to be on the other side of the consumer preference.

In low fraud parameter settings, there are many neighborhoods with no fraudsters in them at all. Their utility gains can cancel out any utility losses from neighborhoods where fraud causes such losses. (Recall that all of our data are average consumer utilities per time step.) The probability of a neighborhood having no fraudsters is \( P(fraud = 0) = (1 - p)^9 \) where \( p \) is the fraud rate. Given our 529 neighborhoods, the expected number of fraud-free neighborhoods lose their majority status when the fraud rate is greater than 7.4% and drops below 1 when the fraud rate reaches approximately 50%. Figure 6 shows the present value distributions of our results where at least one neighborhood is expected to be fraud free (i.e. all results through \( \alpha \cdot \beta \cdot 0.4 \)). We can see from this that going from a majority fraud-free economy to one with a minority of fraud-free neighborhoods results in large utility declines.

In the endogenous experiments, firms that commit fraud are never doing better than their neighbors, due to the zero revenue trigger requirement. This means that the second scenario will never add to utility in the endogenous experiments. However, this is not necessarily the case in the stochastic experiments. In the stochastic case, there is no guarantee that the fraudsters will be performing poorly. At the one extreme where all firms have the capacity to commit fraud (i.e. \( \alpha = 1 \)), the mix of attribute strategies of the fraudsters in any one period will, in expectation, reflect the mix of the overall firm population. As the relative weighting within \( \alpha \cdot \beta \) shifts towards \( \beta \), the fraudster mix of strategies has more capacity to diverge from that of the honest population.

We can see some aspects of how the fraudster strategy quality changes over time in stochastic models by understanding more fully how the \( \alpha \cdot \beta \) measure translates to the fraud rate. For the most part, the fraud rate is composed of relatively straightforward parts: it is determined by the selection of \( \alpha \) and \( \beta \), though there will be sampling selection variation for \( \alpha \) between runs and for \( \beta \) between time steps. There is one additional relevant factor in the overall fraud rate in the stochastic experiments: since fraud is assigned stochastically, there will be some cases in every run.
Figure 6: The role of fraud-free neighborhoods in improving average consumer utility. Figure compares the fraud-free environment (circles) to pooled data from each behavioral regime where the expected fraud rate implied a majority or minority of learning neighborhoods would be fraud-free in each period (triangles and square respectively).
where a firm that is actually earning the maximum possible revenue will be selected to commit fraud. In this case, the report is actually true, since the firm has in fact earned revenue from the sale of nine units of the good. Since the firm is reporting truthfully, it is not be included in the measurement of fraud rates.

The changes in real fraud rate over time in the stochastic experiments aren’t interesting because of the magnitude of fraud change involved—they are quite small. Instead, these changes give us an indirect insight into the density of firms producing desirable goods and how that is changing over the course of the run. Figure 7 maps the real fraud rate in the two stochastic experiments when $\alpha \cdot \beta = 0.6$ to the utility level for each timestep, averaged across the 50 runs of the parameter settings. Those points are then connected in chronological order, starting at $t = 1$ with a utility of approximately 0.

The hook shape in most of the stochastic cases shows how the real fraud rate increases initially as the source of utility shifts from “lucky” firms that randomly drew a relatively good attribute in $t=1$ to a broader population of learners (and utility declines because more firms are being misguided than are learning good info). Then, slowly, a few firms discover preferences that are close on target, providing near-maximum utility for most consumers, but the rest of the firms may or may not improve their strategies. The stochastic cover-up case where $\beta = 1$ behaves differently: since the fraudsters never change their strategy here, any who earned the maximum feasible revenue in the first few time steps due to luck will lose at least some of that revenue eventually. In this case, the real fraud rate converges on the potential fraud rate.

For the third source of utility increases to be relevant, the only firms that can compete with fraudsters in terms of inducing other firms to move towards their attribute strategy are firms who are actually earning top revenues. A firm will earn all nine of its potential customers if it is producing the most desirable product in a $5 \times 5$ square. In the previous example, we see evidence of potential fraudsters earning top revenue, but this could also occur for a firm that does not have the potential to commit fraud.

Top earning firms tend to be stable top earners when they are producing goods with an attribute very close to the ideal 0.32. Once a firm earns from all nine of its potential consumers, it will not change strategies until its sales decline, since ties in top reported revenue between oneself and another firm result a firm continuing with its own strategy in all experiments. If it is in a high-fraud area, it is a particularly stable maximum earner, since other firms are likely to be influenced often enough by fraudsters to be unable to converge on a competitive strategy.

The persistence of these top earners can help explain why, particularly in the stochastic high fraud cases, even though utility initially declines it turns around part way through the run and begins to climb again. This is most strikingly illustrated by the stochastic cover-up experiment in those parameter settings where $\beta \neq 1$. Figure 8 shows the mean utility levels for each such settings. In this figure, the higher fraud rates take longer to reach their minimum and turn around,

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6The fraud rates have also been smoothed by taking a 25 period moving average. This reduces the random variation significantly, allowing the structure to be more visible.
Figure 7: Examples of average stochastic fraud rates’ relationship with utility over time. Fraud rates have been smoothed with a 25 time-step moving average. Starting points indicated by open symbols, finishing points marked by closed symbols. Each line represents mean of 50 trials.
but every one does. These turn-arounds occur because the true top earners are able to move some of the non-fraudsters in each period towards their attribute. The movement is very slow, since the poorly performing fraudsters also exert attraction. But the true earners are more persistent than the fraudsters (since $\beta \neq 1$), and in every period that a firm is not covering up its fraud it has a positive probability of moving towards the desired attribute.

The final source for utility improvement can, in some respects, be considered an artifact of the model design. Since we have a one dimensional attribute, the optimal attribute is not at a boundary, and firms move halfway from their previous attribute to their target attribute (plus a small error term), there is always a chance that 0.32 lies close to that halfway mark between starting and target attribute. To the extent that it does, utility will increase. This is most likely to be the case when a neighborhood has a wide variety of attributes—something that generally happens only at the beginning of a run. If one returns to Figure 5, in all four experiments there is a sharp increase in utility from $t = 1$ to $t = 2$. This is largely due to this averaging effect. We performed some smaller parameter sweeps (not reported here) which also vary the consumers’ preferences and

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Figure 8: Mean utility levels per time step for all Stochastic Cover-up trials with parameter settings where $\beta \neq 1$.  

the adjustment factor. They demonstrate that if the weight, \( \lambda \), placed on the target attribute is closer to one or if the consumer preference is closer to the attribute boundary, this initial uptick in utility at higher fraud levels disappears.

The averaging effect can have a longer influence in cases where there is persistent fraud at multiple firms in the neighborhood. The initial positions of these fraudsters will be drawn from the full uniform distribution and will be widely spread. Particularly if the fraudsters are able to update their strategies, as in the Change experiments, they will be drawn randomly towards different fraudsters in their neighborhood in each period. While the process is slow, this will allow for a relatively effective search of the space eventually, and if one firm does discover a real source of high revenues, it will begin to exert additional influence in the manner discussed above. It is this dynamic that allows the stochastic change high fraud trials to eventually reach utility levels that are not much below that of the fraud-free levels. Interestingly, in the long run of the stochastic change experiment, the runs with \( \beta = 1 \) and expected fraud rates of approximately 20% perform the worst. This is because these parameter settings maximize the number of neighborhoods with exactly one or two fraudsters, which are the least likely neighborhoods to converge on the desired attribute.

In contrast to the stochastic experiments, the endogenous experiments really do not have access to the last three sources of utility improvement—at least not for very long. As already discussed, the fraudsters must be doing poorly in order to trigger the endogenous fraud, which eliminates the second option. And as soon as a fraudster begins to attract even lower levels of revenue, the firm stops committing fraud and, if there is another active fraudster in the neighborhood (by definition producing a less desirable good) the former fraudster will start to follow the active fraudster. The averaging effect is less likely to occur as well, since the dominant pulls will always be to the boundaries of the attribute possibilities.

As we have discussed in several of the issues raised above, the critical issue is how many fraudsters reside in a particular neighborhood. While the expected number is a function of the fraud rate, the utility path a particular economy takes will be quite dependent on the initial distribution of fraudsters across the geographical space. It appears, however, the average utility of the first timestep is much less important. In otherwords, the distribution of the first attribute selections has little long run effect. The only exception is in higher levels of the stochastic cover-up experiment, where few firms change strategies in any time step, so the movement away from the initial conditions is very slow. For the other trials, the predictive strength of the initial conditions has mostly faded after only ten timesteps.\(^7\)

\(^7\)This may seem to contradict the need to control for the initial utility in the present value calculations. This is not the case, however, since the utility of the first step or two has a non-trivial effect on the overall present value calculation, given that the discounting weights the early timesteps.
6 Conclusions

This paper demonstrates that the search for significant social costs due to fraud should not be limited to the fraudster’s shareholders. Instead, information about a company’s profits plays an important role in the economic learning of the entire industry, and when that information is distorted, it can disrupt industry convergence on the optimal outcome. At the lowest levels of fraud, this disruption is relatively modest. As the fraud rates climb, the effects become more severe and are more sensitive to the exact details of the fraud generation and learning processes, as well as to initial conditions.

Our model offers a baseline case that establishes significant utility loss in an economy with fraud and relatively unsophisticated players. Future research will help establish how these effects change in the presence of skepticism, bankruptcy, memory, heterogeneous or changing preferences, etc. Even our simple model provides some significant insights, however.

Beyond the basic observation that financial statement fraud potentially does have social costs, we can see that:

Observation 1 If there is a relationship between the poor performance of a firm and its propensity to commit fraud, particularly misleading information is injected into the system.

In our model, such relationships translates to the endogenous fraud cases. This is relevant to real-world scenarios where the risks to fraud are worth undertaking only if the firm is performing particularly poorly, but once an executive decides to commit fraud it pays off to make the firm look particularly good.

Observation 2 Fraudsters themselves can operate as important conduits of information if they update their strategies based on their private, truthful information, particularly if their neighborhood contains a diverse set of attribute strategies.

If fraudsters cover up their fraud by not adjusting strategies, not only are they denying themselves the opportunity to learn, they also block opportunities for their neighbors who might be following their strategy to improve. They both exert a pull on their neighbors that is difficult to compete with and do not alter their production strategies, thereby continuing to propagate the same misinformation. When a fraudster is willing to update on the basis of private information, in almost all cases this can significantly reduce the harm caused by the fraud. While the fraudster continues to exert a pull on his neighbors, one of two things may occur.

In a low fraud neighborhood, a single fraudster willing to adjust strategies according to his private information is essentially operating in a fraud-free environment, able to pursue any improvements suggested by his neighbors’ experiences. This improvement in information is then passed on to the neighborhood, albeit with a one time-step lag. This scenario does cause more harm than the delay, however. The fraudster can only incorporate the information about the strategies that exist in his neighborhood, but the diversity of strategies in the area is being reduced quickly by the
fraud. If the neighborhood converges on the fraudster’s strategy before the fraudster can discover the optimal strategy, further learning is significantly reduced.

In neighborhoods with several fraudsters, no one has a fraud-free view, but the presence of multiple, moving fraudsters providing conflicting information about the best strategy will maintain a diverse set of strategies long enough, in some cases, to search the strategy space reasonably thoroughly. This learning process is extremely slow, but does provide some opportunity for long run improvements in utility even at high fraud rates.

Observation 3 *Interruption fraud is comparatively harmless. Persistent fraud within a neighborhood is far more damaging.*

If fraud is intermittent in a neighborhood, the neighborhood can make significant strides towards the desired attribute in the fraud-free periods. This then narrows the scope for how far fraudsters will pull their neighbors away from the ideal, since the fraudsters will have moved along with everyone else much closer to the ideal attribute during the fraud-free period. In contrast, neighborhoods with persistent fraud can become islands of particularly bad information.

Even when the fraud rates are high enough that a neighborhood is rarely fraud-free, if the particular culprit changes from period to period, there is a greater diversity in the misleading signals. As discussed in the previous observation, this increases the ability of firms to search a broader space of strategies and therefore the likelihood of stumbling across a successful one.

Observation 4 *Second to a zero-fraud environment, a system that maintains a diverse set of attribute strategies tends to promote consumer welfare.*

A common theme in all our observations is the value of a diverse set of strategies in offsetting the harm of fraud. Even the random strategy draw at the first time step performs quite well, relative to some of the reachable utility levels in, particularly, the endogenous experiments. Even at higher levels of fraud, if the fraudsters are relatively diverse, as in the stochastic cases, the random search process can lead to good outcomes, albeit slowly. If the fraudsters are not as diverse, as in the endogenous cases, there is little opportunity for the system to discover the desired attribute.

Observation 5 *The driving dynamic is the number of fraudsters “visible” to each other, and the number of neighborhoods with fraudsters, not the fraud rate per se.*

The mapping of a specific fraud rate to a utility outcome relies on how the population is divided into neighborhoods. This experiment kept that number fixed, but it is clear from our analysis of the underlying mechanisms that a fraud rate of 5%, which has relatively modest effects on utility across all four of our experiments, would have a significantly different, and more detrimental, effect were neighborhoods larger than the current nine firms. As our work is translated to applied settings, therefore, the mass of fraudsters who respond to each other is more important than any assessment of an overall fraud rate.
Observation 6  *Predicting how the above dynamics will interact is difficult and sensitive to the exact model specifications.*

This final observation implies that understanding the effects of fraud or other forms of misinformation on economic learning in a specific policy scenario will require a fairly detailed understanding of the levels of misinformation and how the purveyors of misinformation update their strategies. It is not simply enough to be satisfied with a policy that reduces fraud rates, for example. It is possible to construct scenarios where policy interventions could be counter-productive: if, for example, a policy reduced overall fraud rates but did so in such a way as to encourage a smaller number of more persistent, repeat offenders.

This paper can only make the case that our understanding of how fraud, and misinformation more broadly, affect economic learning is of significant enough import to deserve further investigation. Limiting policy concerns to the effect of fraud on a company’s shareholders is myopic and does not help articulate the case for the importance of fraud prevention. The central role good information plays in successful adoption of improved business strategies or technologies makes a far more compelling case for fraud prevention and other efforts to ensure that economic success is accurately broadcast to the marketplace.


