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Patterns of Collusion in the U.S. Crop Insurance Program: An Empirical Analysis

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This article analyzes anomalous patterns of agent, adjuster, and producer claim outcomes and determines the most likely pattern of collusion that is suggestive of fraud, waste, and abuse in the federal crop insurance program. Log–linear analysis of Poisson-distributed counts of anomalous entities is used to examine potential patterns of collusion. The most likely pattern of collusion present in the crop insurance program is where agents, adjusters, and producers nonrecursively interact with each other to coordinate their behavior. However, if *a priori* an intermediary is known to initiate and coordinate the collusion, a pattern where the producer acts as the intermediary is the most likely pattern of collusion evidenced in the data. These results have important implications for insurance program design and compliance.

Key Words: abuse, collusion, crop insurance, empirical analysis, fraud, waste

JEL Classifications: G22, Q12, Q18, Q19

Since the early 1990s, the need to reduce fraud, waste, and abuse in the U.S. crop insurance program has been a recognized priority of the United States Congress, the United States Department of Agriculture (USDA), the USDA's Risk Management Agency (RMA), and the private crop insurance companies. Accordingly, in the debates prior to the approval of the Agriculture Risk Protection Act (ARPA) of 2000, a major issue was how to further combat fraud, waste, and abuse in the crop insurance program. Enough concerns were raised during the debates that Congress included several sections dedicated to expanding and strengthening the anti-fraud authorities of the RMA and approved private insurance providers.

As part of the legislation, data warehousing and data mining techniques were explicitly identified as tools to be used in identifying agents, adjusters, and producers that exhibit "anomalous" claim outcomes. Anomalous outcomes are defined as outcomes that are equal to or greater than 150% of the mean claim outcome in a designated area. For example, agents are deemed anomalous if their loss claims are equal to or greater than 150% of the mean loss claims in the same area.[1] Al-

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[1] See Section 515(j) and 515(d) of the ARPA of 2000.

though these definitions are not *prima facie* evidence for fraud, waste, or abuse, they are indicators of anomalous outcomes that are suggestive of fraud, waste, and abuse. Given the definitions above, simple outlier detection techniques can identify individual agents, adjusters, and producers that exhibit anomalous outcomes. However, these simple techniques by themselves cannot give further insight about the potential structure of fraud, waste, and abuse undertaken by these individuals.

Knowledge about the potential structure or pattern of collusion among these three entities will provide insights to policymakers on how to better design provisions and policies in the crop insurance program that can reduce the incentives for fraud, waste, and abuse. Better provisions and design of the program would then reduce taxpayer dollars that can potentially be lost because of fraudulent, wasteful, and abusive acts. Academicians will also benefit from better understanding of the pattern of collusion in the crop insurance program. With the knowledge of the pattern of collusion, academics can better model the behavior of the individuals involved in the collusion. Theoretical studies related to finding optimal contract form and optimal penalty structures can be better designed and better studied if we know which pattern of collusive behavior is more prevalent in the crop insurance program. For example, if the prevalent collusion structure is only between adjuster and producer, then academics can focus on finding optimal contracts or penalty structures for this pattern. Thus, academic resources would not be wasted on modeling other structures that might not be truly evident in crop insurance. Results from these academic studies will then be more useful to policymakers because the underlying behavioral structure of these theoretical models is based on what is really evident in crop insurance data.

Furthermore, knowledge about the structure of collusion would also provide important insights to compliance offices on what patterns of anomalous outcomes to look for in investigating potentially fraudulent claims. For example, some RMA compliance investigators currently believe that the structure of collusion in the insurance program is configured as a "cart wheel" conspiracy. The "cart wheel" model of collusion is founded on the principle of linked actions from a central group of conspirators (cart wheel hub) through a spiraling network of conspiracy intermediaries (spokes in the wheel) relayed for action to many performing players (the rim). On the basis of cases that have been successfully investigated, these investigators observed that agents may be the "hub," adjusters may be the "spokes," and the producers may be the "rim." This is the type of collusion pattern that investigators flag for further investigations. An analysis of patterns of collusion based on claims data will provide information that may support the existence of this type of collusion pattern. Allocation of investigative resources will improve because instead of ad hoc allocations, resources can be prioritized to first explore the agents, adjusters, and producers that follow patterns suggestive of collusion.

There are no empirical studies in the literature that have examined potential patterns of collusion that is suggestive of fraud, waste, and abuse in the U.S. crop insurance program. The limited economic literature about collusion to commit fraud in insurance markets has been theoretical in nature and is usually aimed at finding optimal contracts to mitigate this behavior (Alger and Ma; Picard). These theoretical studies also mainly focused on collusive behavior between two parties, unlike the crop insurance case where there may be three parties involved—agents, adjusters, and producers.

Since there have been no studies on collusion in the crop insurance market and with the potential importance of this knowledge to academics, policymakers, and compliance people, this article aims to analyze anomalous patterns of agent, adjuster, and farmer claim outcomes and determine the most likely pattern of collusion that is suggestive of fraud, waste, and abuse in the U.S. crop insurance program. The paper proceeds as follows. The next section provides some background and discussion on the potential causes, incentives, and penalties associated with collusion. The hypotheses, empirical methods, results, and conclusions are discussed in the remaining three sections.

Collusion in the U.S. Crop Insurance Program: A Conceptual Framework

This section presents a conceptual framework that elucidates the incentives for producers, adjusters, and agents to collude to defraud or abuse (or both) the U.S crop insurance program when a loss occurs. Let us first start with the producers. Define the producer's actual revenues at harvest (R^a) as $R^a = Y^aP^a$, where Y^a is the actual yield at harvest and P^a is the actual price received. The actual production cost is C^a. Assume that a producer has initial wealth W and has bought an Actual Production History (APH) crop insurance policy for which the producer has to pay t in premiums.[2] The producer will receive an indemnity I when a loss (γ) occurs. That is, actual yield (Y^a) falls below the insured or guaranteed yield Y^g. The guaranteed yield is determined by multiplying the coverage level (δ) and the average yield history (Y^e) of the producer (i.e., $Y^g = \delta Y^e$). The indemnifiable loss (γ) can then be defined as $\gamma = Y^g - Y^a$. Thus, the indemnity is a function of the loss [i.e., $I(\gamma)$].[3]

In view of the foregoing, the producer's final wealth when a loss occurs can be represented by $W_f = W + R^a - C^a + I - t$. Assume that a risk-averse producer's utility is a function of his final wealth $U(W_f)$, where $U(\cdot)$ is a twice-differentiable von Neumann Morgenstern utility function having the following derivative properties: $U' > 0$ and $U'' < 0$:

$$(1)\qquad U(W + R^a - C^a + I - t).$$

A producer chooses either to be honest (not commit fraud) or dishonest (commit fraud). Specifically, if a producer chooses to be dishonest and commit fraud, then he can opt to manipulate the size of the loss to his advantage. Then, I is also conditioned on whether or not the farmer commits fraud. One way for the farmer to commit fraud in the crop insurance program is to collude with agents and adjusters to manipulate the size of the loss and increase his indemnity.

If the producer colludes with agents and adjusters, they can manipulate the loss such that the indemnities will be higher compared to when they do not collude, $I^c(\gamma) > I^h(\gamma)$. Hereinafter, the superscripts c and h indicate collusion and honesty, respectively. Assuming that the probability of successful fraud is one ($\theta = 1$), a producer can manipulate the loss γ to get the maximum indemnity possible when he/she colludes. Thus, a producer has the incentive to collude and manipulate the reported loss, if the probability of successful fraud is equal to one.

Now assume that the probability of successful fraud is θ (where $0 \leq \theta \leq 1$), even if producers, agents, and adjusters collude. Let the monetary value of penalties when caught be P. A collusive or dishonest producer's expected utility is then:

$$(2)\qquad EU^c = \theta[U^c(W + R^a - C^a + I^c - t)] + (1 - \theta)[U^c(W + R^a - C^a - t - P)].$$

A dishonest producer will have to compare EU^c with U^h and decide whether or not to collude and submit a fraudulent claim. Therefore, if the probability of successful fraud θ is high enough to yield net utility gains in expectation [$EU^C - U^h > 0$], a fraudulent claim may be filed (Allingham and Sandmo; Becker; Srinivasan).[4]

[2] The APH crop insurance policy is an individual yield-based insurance policy. Although this type of policy is the focus here, the results in this conceptual model should apply to revenue policies (e.g., CRC, IP) as well.

[3] The indemnity function for an APH insurance can be mathematically represented as $I = \max\{0, (Y^g - Y^a)P^g\}$, where P^g is the producer's elected price, which is a fixed proportion of USDA's projected farm level price for the crop year. See Harwood et al. for more details on indemnity functions from different crop insurance plans.

[4] Note that an insured producer may also have unobservable "moral" or "ethical" costs of committing fraud that may outweigh the "actual" financial benefits of committing fraud. If this moral cost is high enough, then even if there are financial incentives to collude a producer may choose not to. In this case, [$EU^C - U^h < 0$] because of the moral cost of colluding. This moral cost also applies to agents and adjusters. Although this

Therefore, a dishonest producer will have strong incentives to file a fraudulent claim depending on the magnitudes of θ, I^c, and P. In general, if θ is high, I^c is sufficiently larger than I^h, and P is relatively small, then the producer will have strong economic incentives to collude and not truthfully reveal the loss.[5]

It is important to note that penalties for fraud may also play a role in the producer's incentives to collude. There are several possible penalties that can be imposed on producers caught submitting a fraudulent claim depending on the magnitude of the fraud (i.e., not receiving the indemnity, fines or restitutions, debarment from the insurance program and other government programs, prison time, or any combination of these penalties).[6] However, it is inherently costly and difficult to prove the existence of collusion and to prove that there is indeed fraudulent behavior in crop insurance. Thus, even if the penalties are severe, if the cost of proving the presence of fraud is high and the probability of successfully proving fraud is low, then these penalties may not deter collusion and fraud behavior.

Let us now consider an agent's economic incentives for colluding with producers and adjusters. An agent's payoff or commission depends on the dollar value of the premiums from all insurance policies he sells. The agent is paid a percentage of that total premium (i.e., 20% of total premiums brought in from all the policies sold). An agent's final wealth can be defined as $W_f = W + \rho[\Sigma_i t_i] - C^b$, where W is the initial wealth, ρ is the percentage of total premiums received that goes to the agent (his commission), C^b is the actual cost of doing business, and $\Sigma_i t_i$ is the sum of all premiums from the i producers to whom he sold insurance policies. As with the farmer, a risk-averse agent's utility is a function of his final wealth $U(W_f)$, where $U(\cdot)$ is a twice-differentiable von Neumann Morgenstern utility function having the following derivative properties: $U' > 0$ and $U'' < 0$.

If the agent were honest he would only be able to sell policies to honest producers. Dishonest producers will not want to go to the honest agent because the honest agent will not agree to collude if the producer wants to collude. Thus, the maximum number of customers an honest agent could have is n^h. Let the actual number of customers an honest agent has be represented by n^h_{ha}, where $0 \leq n^h_{ha} \leq n^h$. An honest agent's utility can then be represented as:

$$(3) \qquad U^h\left(W + \rho\left[\sum_{i=1}^{n^h_{ha}} t_i^h\right] - C^b\right),$$

where $0 \leq n^h_{ha} \leq n^h$. On the other hand, if an agent is dishonest he can sell insurance policies to both the dishonest producer and the honest producer. The dishonest agent will truthfully report losses for producers who are honest and if they are not he will collude with dishonest producers and dishonest adjusters to

is an important point, we chose not to explicitly include this term in the utility equations because it does not materially affect the insights from the conceptual framework and would just introduce unnecessary notational clutter.

[5] Note that when $\theta \neq 1$ even with collusion, the optimal magnitude of loss manipulation through collusion may not be at the point where I^c is maximum (as in the case where $\theta = 1$ with collusion). This is intuitive because the magnitude of I^c (relative to county average) is one indicator RMA Compliance uses in auditing policies and potentially detecting fraud. If there is a chance of getting caught given the magnitude of I^c (even if the producer colludes) then it is rational for the dishonest producer to temper the loss manipulation. Therefore, the probability of successful fraud is not exogenous to the magnitude of loss manipulation [i.e., $\theta = f(I)$]. At the other extreme, if $\theta = 0$ even with collusion, then there is no incentive to collude and submit a fraudulent claim. These arguments demonstrate why optimal magnitudes of fraud and incentives for collusion are conditioned on the probability of successful fraud (and vice versa).

[6] The reader is referred to the RMA Compliance Report available at the RMA website for a more detailed description of the penalties for producers, agents, and adjusters who undertook fraud. Penalties for agents and adjusters are similar to those mentioned in the text for producers. An additional penalty that is different for agents and adjusters (as compared to producers) is that insurance companies can withhold compensation. As mentioned by an anonymous reviewer, insurance companies can also refuse to retain loss adjusters they suspect are committing fraud and the companies can also refuse the contract of an agent to write insurance contracts for their company if they suspect fraud (even without proving it). Agents can also lose their licenses for unethical behavior. These items increase the cost for coconspirators without the need to prove the presence of fraud.

misreport the losses. The maximum number of customers a dishonest agent can potentially have is $n = n^{\mathrm{h}} + n^{\mathrm{c}}$. Assume that the actual number of honest producers the dishonest agent has is $n^{\mathrm{h}}_{\mathrm{ca}}$, whereas the actual number of dishonest producers the dishonest agent has is $n^{\mathrm{c}}_{\mathrm{ca}}$. Further assume that $0 \leq n^{\mathrm{h}}_{\mathrm{ca}} \leq n^{\mathrm{h}}$ and $0 \leq n^{\mathrm{c}}_{\mathrm{ca}} \leq n^{\mathrm{c}}$. A dishonest agent's utility can then be defined as:

$$U^{\mathrm{c}}\left(W + \rho\left[\sum_{j=1}^{n^{\mathrm{c}}_{\mathrm{ca}}} t^{\mathrm{c}}_{j} + \sum_{i=1}^{n^{\mathrm{h}}_{\mathrm{ca}}} t^{\mathrm{h}}_{i}\right] - C^{\mathrm{b}}\right). \tag{4}$$

If a dishonest agent gets caught, however, he can face punishment that has a monetary value P. Assume that the probability of successful fraud is $0 \leq \theta \leq 1$, then the dishonest agent's expected utility is

$$\begin{aligned} EU^{\mathrm{c}} = {} & \theta\left\{U^{\mathrm{c}}\left(W + \rho\left[\sum_{j=1}^{N^{\mathrm{c}}_{\mathrm{ca}}} t^{\mathrm{c}}_{j} + \sum_{i=1}^{n^{\mathrm{h}}_{\mathrm{ca}}} t^{\mathrm{h}}_{i}\right] - C^{\mathrm{b}}\right)\right\} \\ & + (1 - \theta) \\ & \times \left\{U^{\mathrm{c}}\left(W + \rho\left[\sum_{j=1}^{n^{\mathrm{c}}_{\mathrm{ca}}} t^{\mathrm{c}}_{j} + \sum_{i=1}^{n^{\mathrm{h}}_{\mathrm{ca}}} t^{\mathrm{h}}_{i}\right] - C^{\mathrm{b}} - P\right)\right\}. \end{aligned} \tag{5}$$

Thus, given that a dishonest agent can potentially have customers from two populations (honest and dishonest producers), an agent has strong incentives to be dishonest because a dishonest agent can have a bigger customer base and can potentially have higher expected utility as long as the probability of successful fraud is high and P is relatively small. With a bigger customer base, a dishonest agent can also have a bigger population from which to target larger farms that typically pay higher premiums (i.e., dishonest agents can service large farms that want to collude, whereas honest agents could not).[7] Furthermore, if an honest producer (currently with an honest agent) decides that he wants to collude and be dishonest, the honest producer will have to move to a dishonest agent and the honest agent will lose a customer. On the other hand, if a dishonest agent has an initially honest producer that suddenly wants to collude and be dishonest, the dishonest agent can accommodate his request and not lose a customer. The prospects of losing customers also give strong incentives for an agent to collude.

From the discussion above, the main benefit of collusion to the agent is the chance to have a bigger customer pool to accumulate premiums from and to target larger farms that would pay higher premium levels. There is anecdotal evidence that agents attract producers to get insurance coverage by telling them that they will assure an indemnity payment if the producer agrees to buy insurance from him and collude to generate a claim. Agents resort to these collusive tactics primarily because they are selling identical insurance products at identical prices

[7] Although agent commissions are typically tied to premiums alone, it is clear from Equations (3), (4), and (5) that commissions also depend on the number of policies sold (even if indirectly). An agent can opt to target larger farms that have bigger premiums, but having more policies sold (in addition to the premiums from bigger farms) will increase the agent's payoff even more. Also, our consultation with several insurance companies reveals that they prefer agents with more policies to agents with fewer policies sold (assuming the total premium they bring in is comparable). This is because a pool of smaller policies is considered less risky than a pool made up of few very large policies. It is also important to note here that insurance companies have the option on how commissions are given to their agents. Different companies have different contract terms in terms of agent commissions. Most companies condition it on total premiums alone, but some companies also condition on loss ratios of the agents (we thank an anonymous reviewer for pointing this out). This means that for certain companies, agent compensation may also be tied to indemnities and the expected underwriting gains, as well as the size of the book of business. As suggested by Picard, the use of loss ratios as a factor to determine agent compensation may reduce the incentives for colluding. In addition, agent compensation structure may even vary within the company so that they can retain the more desirable agents (i.e., better compensation structure for more desirable agents with large book of business and low loss ratio).

(that are mandated by government). Hence, the only way they could compete is through "services," where some agents choose to collude and promise friendly loss adjusters to have an advantage over the competition.

Lastly, let us look at the economic incentives for an adjuster to collude with an agent or producer. An adjuster is an independent contractor that is hired and trained by the insurance company to adjust their customer's claims. An adjuster is theoretically randomly assigned to customers of one particular agent. However, on the basis of our conversations with RMA compliance, agents appear to have a strong influence on the choice of adjusters assigned to them.[8] For example, an agent can usually tell the insurance company that he prefers a particular adjuster because he works well with his customers and that these customers will not stay with the insurance company if the adjuster was not the preferred one.

The ability of agents to influence the choice of adjuster (and the seemingly tolerant behavior of insurance companies to this) can be linked to the incentives created by the Standard Reinsurance Agreement (SRA) in crop insurance. Succinctly, the SRA defines the conditions by which private insurance companies deliver the different crop insurance products and how RMA reinsures these private companies (RMA 1999). The SRA is relevant to the analysis here because it provides a mechanism for crop insurance companies to cede undesirable (high-risk) policies to the RMA, whereby the government shoulders most of the risk.[9] This aspect of the SRA creates incentives that affect the reinsured crop insurance companies' relationships with agents and adjusters. Insurance companies are seemingly tolerant to the influence of agents because the SRA allows them to cede the potentially fraudulent and high-risk policies to the government anyway. Thus, the federal government is taking most of the loss risk and the company has much less incentive to police collusion and fraudulent behavior.[10]

The adjuster is usually paid on the basis of the number of acres he adjusts.[11] The adjuster's final wealth can then be defined as $W_f = W + \Sigma_i s_i(\Sigma_j a_j)_i - C^b$, where s_i is the remuneration he gets per acre adjusted for the insurance company associated with agent i, a_j is the number of acres adjusted for a producer j who is a client of agent I, and C^b is the cost of doing business. Assume that a risk-averse adjuster's utility is a function of his final wealth $U(W_f)$, where $U(\cdot)$ is a twice-differentiable von Neumann Morgenstern utility function having the following derivative properties: $U' > 0$ and $U'' < 0$.

Assume that there are η agents in the crop insurance market such that $\eta = \eta^h + \eta^c$, where η^h are honest agents and η^c are dishonest agents who are willing to collude. An honest adjuster can work for insurance companies with both an honest and a dishonest agent. An honest adjuster assigned to an honest agent can potentially work on all of the honest agent's clients because all his clients/producers will be honest (n^h_{ha}). However, if this honest adjuster works for a dishonest agent he will only be asked to work on the dishonest agent's honest clients/producers (n^h_{ca}), assuming that the agent knows *a priori* that the adjuster is honest. Hence, an honest adjuster's utility function can be represented as:

$$(6) \qquad U^h\left(W + \sum_{i=1}^{\eta^h_{hd}} s_i\left[\sum_{i=1}^{n^h_{ha}} a_j\right]_i + \sum_{i=1}^{\eta^c_{hd}} s_i\left[\sum_{j=1}^{n^h_{ca}} a_j\right]_i - C^b\right),$$

where η^h_{hd} is the number of honest agents to whom the honest adjuster is assigned (0 ≤

[8] Note this behavior is observed in "practice," but the actual "policy" terms of these contracts stipulates that adjusters are randomly assigned and the agent should not have any influence on the choice of adjuster.

[9] The reader is referred to Ker (1999, 2001) and the actual RMA SRA document for a deeper discussion of the SRA stipulations.

[10] We thank one anonymous reviewer for raising this point.

[11] Contract adjusters are also sometimes compensated on a per claim basis, per day basis, or per diem basis. They also usually receive reimbursements for necessary expenses such as travel and lodging. These types of compensation, however, do not change their structure of incentives in the model.

$\eta^h_{hd} \leq \eta^h$) and n^c_{hd} is the number of dishonest agents to whom the honest adjuster is assigned ($0 \leq \eta^c_{hd} \leq \eta^c$).

A dishonest adjuster can also work for both an honest and a dishonest agent. A dishonest adjuster can work with an honest agent by truthfully adjusting losses for this honest agent's honest policyholders (n^h_{ha}). A dishonest adjuster can also work for a dishonest agent, but he can work on all of this dishonest agent's policyholders—both the honest (n^h_{ca}) and dishonest (n^c_{ca}) policyholders. Comparing this to the honest adjuster, an honest adjuster can only work on the dishonest agent's honest policyholders, but not the dishonest producers or policyholders. Therefore, a dishonest adjuster's utility can then be represented as

$$(7)\quad U^c\Bigg(W + \sum_{i=1}^{\eta^h_{cd}} s_i\left[\sum_{j=1}^{n^h_{ha}} a_j\right]_i + \sum_{i=1}^{\eta^c_{cd}} s_i\left[\sum_{j=1}^{n^h_{ca}} a_j\right]_i + \sum_{i=1}^{\eta^c_{cd}} s_i\left[2\sum_{j=1}^{n^c_{ca}} a_j\right] - C^b\Bigg),$$

where η^h_{cd} is the number of dishonest agents assigned with the honest adjuster ($0 \leq \eta^h_{cd} \leq \eta^h$) and η^c_{cd} is the number of dishonest agents assigned with the dishonest adjuster ($0 \leq \eta^c_{cd} \leq \eta^c$).

If a dishonest adjuster gets caught, however, he can face punishment that has a monetary value P. Assume that the probability of successful fraud is $0 \leq \theta \leq 1$; then the dishonest agent's expected utility is

$$(8)\quad EU^c = \theta\Bigg\{U^c\Bigg(W + \sum_{i=1}^{\eta^h_{cd}} s_i\left[2\sum_{j=1}^{n^h_{ha}} a_j\right]_i + \sum_{i=1}^{\eta^c_{cd}} s_i\left[\sum_{j=1}^{n^h_{ca}} a_j\right]_i + \sum_{i=1}^{\eta^c_{cd}} s_i\left[\sum_{j=1}^{n^c_{ca}} a_j\right] - C^b\Bigg)\Bigg\} + (1-\theta) \times \Bigg\{U^c\Bigg(W + \sum_{i=1}^{\eta^h_{cd}} s_i\left[\sum_{j=1}^{n^h_{ha}} a_j\right]_i + \sum_{i=1}^{\eta^c_{cd}} s_i\left[2\sum_{j=1}^{n^h_{ca}} a_j\right]_i + \sum_{i=1}^{\eta^c_{cd}} s_i\left[\sum_{j=1}^{n^c_{ca}} a_j\right] - C^b - P\Bigg)\Bigg\}.$$

Therefore, if the probability of successful fraud is high and P is relatively small, an adjuster has strong incentives to collude because he can potentially work on three populations—honest agent–honest producer, dishonest agent–honest producer, and dishonest agent–dishonest producer. On the other hand, an adjuster that does not collude can only potentially work with two populations—honest agent–honest producers and dishonest agent–honest producer. A dishonest adjuster will have a bigger customer base. Therefore, if an adjuster has more populations to work with, he has the potential to adjust more acres and to earn more money—which leads to more incentives to collude and to help file fraudulent claims. The opportunity to adjust more acres and earn more money is the main benefit of collusion to adjusters.

Aside from the incentives described above, another potential incentive for agents and adjusters to collude is the opportunity to enter into a "side-contract" with the producers. In this case, agents and adjusters can potentially receive more "compensation" for their collusion. Producers can form an agreement with agents and adjusters such that part of the excess indemnity generated from the false claim will be paid to the colluding agent and adjuster, if their fraud scheme succeeds. This potential for "side-payments" also creates incentives for agents and adjusters to collude.

Hypotheses and Empirical Framework

The discussion in the previous section suggests that producers, agents, and adjusters may have individual incentives for colluding and undermining the integrity of the U.S. crop insurance program. Although there are individual incentives for collusion, the pattern of collusion that arises from these incentives is not well understood. There are anecdotal notions from RMA compliance as to what pattern of collusion is most likely (i.e., cart wheel hypothesis), but there have been no empirical studies that examined whether this pattern or other alternative patterns can be supported by data.

Since this paper aims to provide evidence

Table 1. Hypothesized Collusion Patterns

Null Hypothesis:
H_0: No statistically significant relationship exists between the agent, adjuster, and producer nodes.
Collusion with Intermediary Hypotheses:
H_{A1}: A statistically significant relationship exists where: agent $\leftrightarrow$ adjuster $\leftrightarrow$ producer.[a]
H_{A2}: A statistically significant relationship exists where: agent $\leftrightarrow$ producer $\leftrightarrow$ adjuster.
H_{A3}: A statistically significant relationship exists where: adjuster $\leftrightarrow$ agent $\leftrightarrow$ producer.
Nonrecursive Triplet Hypothesis:
H_{A4}: A statistically significant nonrecursive relationship exists linking all nodes to all nodes: Agent is linked to producer and adjuster nodes, producer is linked to agent and adjuster nodes, and adjuster is linked to producer and agent nodes.
Additional Doublet Hypotheses:
H_{A5}: A statistically significant relationship exists between adjuster and producer.
H_{A6}: A statistically significant relationship exists between adjuster and agent.
H_{A7}: A statistically significant relationship exists between agent and producer.

[a] Cart wheel conspiracy hypothesis.

about the potential pattern of collusion present in the crop insurance program, we have to test several hypotheses. The null hypothesis of this analysis is that there is no collusion—anomalous claim outcomes of agents, adjusters, and producers are independent (Table 1). Since we are interested in patterns of collusion, there are four alternative patterns of collusion among the three entities that are examined in this paper. From Table 1, the first three alternative hypotheses are "collusion with intermediary" patterns: H_{A1}: agent $\leftrightarrow$ adjuster $\leftrightarrow$ producer; H_{A2}: agent $\leftrightarrow$ producer $\leftrightarrow$ adjuster; and H_{A3}: adjuster $\leftrightarrow$ agent $\leftrightarrow$ producer. Note that the "cart wheel" pattern of collusion that RMA compliance investigators subjectively believe in is H_{A1}: agent $\leftrightarrow$ adjuster $\leftrightarrow$ producer. The last alternative hypothesis we test in this paper is the case where the agent, adjuster, and producer are linked to one another nonrecursively, as opposed to the first three alternative hypotheses where there is an intermediary that links with the two other partners in the collusion (Gilbert). Moreover, in the doublets hypotheses, we also examine the presence and strength of collusion between only two individuals rather than three: H_{A5}: adjuster–producer; H_{A6}: adjuster–agent; and H_{A7}: agent–producer (Table 1).

The ideal data needed to test the hypotheses above are actual frequency counts of agents, adjusters, and producers that have been caught committing fraud. These counts of fraudulent behavior can then be empirically tested to see whether there is association among the fraud counts of agents, adjusters, and producers. Presence of statistically significant association of fraud counts among the entities suggests the presence of collusion. Unfortunately, frequency count data of actual fraud behavior is not available at this time. Therefore, counts of "anomalous" agents, adjusters, and producers are used in this study, instead of actual counts of individuals caught committing fraud.

To flag anomalous entities, we used RMA data for reinsurance years 1998, 1999, and 2000, for all producers and insurance plans [i.e., Multiple Peril Crop Insurance, Crop Revenue Coverage (CRC), Income Protection (IP), etc.]. Catastrophic (CAT) insurance policies are excluded from the analysis.[12] Counts of "anomalous" entities are generated on the basis of specific threshold levels and specific indicator variables. On the basis of ARPA of 2000, the mandated criteria for flagging anomalous agents, adjusters, and producers is

[12] CAT policies are excluded because premiums for these policies are fully subsidized by the government and only require a flat fee and the loss ratio used to flag anomalous outcomes cannot be computed.

Table 2. Indicators of Anomalous Outcomes

Indicators	Relevant to:
Ratio 1 = \$ Indemnity/\$ Premium	Adjuster, Agent, Producer
Ratio 2 = \$ Indemnity/\$ Liability	Adjuster, Agent, Producer
Ratio 3 = # Loss Policies/Total # Sold	Agent
Ratio 4 = # Loss Units/Total # Units Insured	Agent
Ratio 5 = \$ Adjuster$_i$/\$ County Indemnity	Adjuster
Ratio 6 = # Claims Adjuster$_i$/Total County Claims	Adjuster

whether claim outcomes are equal to or greater than 150% of the mean outcome in a designated area. In this study, we first use the mandated 150% threshold level to generate counts of anomalous entities, but we also generate counts using a 200% threshold for comparison. Another criterion that we use to flag anomalous individuals is whether their claim outcome is one or two standard deviations away from the mean outcome in the area. Using standard deviation is a more statistically based threshold as compared to the arbitrary 150% threshold. The use of several threshold levels and types enables us to examine whether our results are robust to different flagging criteria. The "designated area" used in the flagging procedures above is at the county level.

In consultation with the RMA compliance division, six indicator variables are used to identify anomalous agent, adjuster, and producer claim outcomes, where some indicators are applicable to all three and others are applicable only to an agent or adjuster separately (Table 2). Experienced RMA compliance investigators initially suggested several indicator variables that they believe were "reasonable" and can provide unique information (i.e., least duplicitous) to the detection of anomalous behavior. From the initial set of indicators provided, we worked in consultation with these RMA compliance investigators to select the six indicator variables chosen for this study.

If the value of the indicator for an agent, adjuster, or producer exceeds the specific thresholds discussed above, then that agent, adjuster, or producer is flagged (flagged = 1; not flagged = 0). Note, however, that a particular agent, adjuster, or producer is only deemed anomalous if *all* the applicable indicators are flagged. As an example, the Appendix tables show the 2 × 2 × 2 multiway contingency table of anomalous agent, adjuster, or producer policies that are flagged using the 150% threshold for 1998, 1999, and 2000 (See Appendix Tables 1–3). The multiway contingency tables for the other flagging thresholds are not reported here, but are available from the authors upon request.

On the basis of the agents, adjusters, and producers identified as anomalous, a log–linear analysis is used to test the hypotheses about the patterns of collusion in the U.S. crop insurance market. Log–linear analysis is appropriate because it provides a flexible mechanism for the analysis of Poisson-distributed count data (i.e., number flagged as anomalous versus number not flagged as anomalous). Log–linear analysis is a statistical technique that allows one to formally test the association patterns among categorical variables (Agresti). It is a procedure that can easily handle multiway contingency tables and test whether the frequencies of the categorical variables have a pattern of association (McCullagh and Nelder; Nelder and Wedderburn). A statistically significant pattern of association among the counts of anomalous entities is suggestive of collusion. This means that the occurrence of anomalous losses for agents, adjusters, and producers are statistically linked and are not independent. This linkage, therefore, is suggestive of collusive behavior aimed to undermine the integrity of the U.S. crop insurance program.

As mentioned above, the number of flagged anomalous agents, adjusters, and producers are count data and are Poisson distributed:

$$(9) \quad \Pr(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}; \qquad y = 0, 1, 2, \ldots, n,$$

where y is the counts of anomalous claim outcomes with no finite upper limit and μ is the mean $[E(y)]$. The associated Poisson log-likelihood function is as follows:

$$(10) \quad L(\boldsymbol{\mu}, \mathbf{y}) = \sum (y_i \ln \mu_i - \mu_i).$$

Thus, the associated deviance function can be expressed as

$$(11) \quad D(\mathbf{y}, \boldsymbol{\mu}) = 2L(\mathbf{y}, \mathbf{y}) - 2L(\boldsymbol{\mu}, \mathbf{y})$$

$$(12) \quad = 2 \sum [y_i \ln(y_i/\mu_i) - (y_i - \mu_i)].$$

If a constant term is included in the model it can be shown that $\Sigma (y_i - \hat{\mu}_i) = 0$, so that $D(\mathbf{y}; \hat{\boldsymbol{\mu}})$ may then be written in the more usual form $2 \Sigma y_i \ln(y_i/\hat{\mu}_i)$ and is χ^2 distributed. The calculated deviance statistic $D(\mathbf{y}, \boldsymbol{\mu})$ or $D(\mathbf{y}; \hat{\boldsymbol{\mu}})$ is a measure of goodness-of-fit and gives information about the discrepancy of fit between the model and the data.

For each of the hypotheses in Table 1, a log–linear model is specified and estimated. Note that in a log–linear model the cell frequencies in the contingency table are first converted to their natural logarithms and the value in a cell is considered to be a linear combination of an overall mean plus the column and row effects (or parameters). Thus, the label log–linear. Maximum-likelihood estimates of the model parameters are then derived using an iterative weighted least-squares procedure, which is a variant of the Newton–Raphson scoring method (McCullagh and Nelder). A deviance statistic for each is then computed to evaluate which model best fits the data.

The base model, which coincides with the null hypothesis, is where the flagged anomalous agent, adjuster, and producer are independent of each other (i.e., there is no interaction between any of the nodes that might explain counts of anomalous outcomes):

$$(13) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C},$$

where F_{ij} is the log of the expected cell frequency of the cases for cell ij in the contingency table, μ is the overall mean of the natural log of the expected frequencies, and the λ terms are the "effects" that the variables have on cell frequencies (i.e., λ_i^{A} is the agent effect, λ_j^{B} is the adjuster effect, and λ_k^{C} is the producer effect).

The cart wheel hypothesis (H_{A1}), where adjusters serve as the intermediary between the agents and producers, can be expressed as:

$$(14) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C} + \lambda_{ij}^{AB} + \lambda_{jk}^{BC}.$$

This model suggests that a pattern of significant interaction between adjusters and agents (AB), as well as adjusters and producers (BC), exists to further explain the anomalous outcomes flagged in the data. The two other collusion with intermediary hypotheses (H_{A2} and H_{A3}) can also be expressed, respectively, as:

$$(15) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C} + \lambda_{ik}^{AC} + \lambda_{jk}^{BC},$$

and

$$(16) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C} + \lambda_{ij}^{AB} + \lambda_{ik}^{AC}.$$

The nonrecursive triplet hypothesis (H_{A4}), on the other hand, can be expressed as:

$$(17) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C} + \lambda_{ij}^{AB} + \lambda_{ik}^{AC} + \lambda_{jk}^{BC}.$$

Lastly, the additional doublet hypotheses (H_{A5}, H_{A6}, and H_{A7}) are modeled as follows:

$$(18) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C} + \lambda_{jk}^{BC},$$

$$(19) \quad \ln(F_{ij}) = \mu + \lambda_i^{A};+t3\, \lambda_j^{B} + \lambda_k^{C} + \lambda_{ij}^{AB}, \text{ and}$$

$$(20) \quad \ln(F_{ij}) = \mu + \lambda_i^{A} + \lambda_j^{B} + \lambda_k^{C} + \lambda_{ik}^{AC}.$$

Note that the log–linear analysis used here tests the existence of paths of association and not causation. It only identifies the paths of association that best fit the data. The variables investigated in the log–linear models are all treated as "response variables" and no distinction is made between independent and dependent variables. Thus, this procedure allows us to statistically test which pattern of collu-

Table 3. Results of the Log–Linear Analysis Using the 150% Flagging Criterion, RYs 1998–2000

Model	RY 1998			RY 1999			RY 2000		
	Deviance	*df*	Rank	Deviance	*df*	Rank	Deviance	*df*	Rank
Null	6,401.78	4		7,117.15	4		7,959.36	4	
Collusion with Intermediary									
(1) agent ↔ adjuster ↔ producer	1,493.09	2	3	1,709.59	2	3	1,781.44	2	3
(2) agent ↔ producer ↔ adjuster	231.32	2	2	405.74	2	2	310.42	2	2
(3) adjuster ↔ agent ↔ producer	3,963.98	2	5	4,166.63	2	5	5,048.59	2	5
Nonrecursive Triplet									
(4) triplet	0.66	1	1	4.45	1	1	0.44	1	1
Doublets									
(5) adjuster–producer	2,081.11	3	4	2,532.92	3	4	2,501.31	3	4
(6) adjuster–agent	5,813.77	3	7	6,293.82	3	7	7,239.48	3	7
(7) agent–producer	4,551.99	3	6	4,989.97	3	6	5,768.47	3	6

Notes: All results are significant at $P < 0.0001$. Statistic is Chi-square distributed −2 log likelihood. RY is reinsurance year; *df* is degrees of freedom.

sion is more evident in the data on the basis of the counts of anomalous outcomes.

Results

Results of the log–linear analysis using the 150% flagging criterion are presented in Table 3. Overall, the pattern of collusion that best fits the data is the nonrecursive triplet where the agent, adjuster, and producer are linked to one another nonrecursively. This pattern of collusion is consistently the best fit over the time period under consideration (1998–2000). This result indicates that nonrecursive communication and sharing of information among the three entities may best explain the counts of anomalous outcomes found in the data over the period 1998–2000. Coordinated behavior between the three entities seems to be the pattern of collusion that most likely enables these entities to violate the integrity of the federal crop insurance program. Each entity has incentive to collude and a nonrecursive pattern of collusion among all entities is evident in the data. Therefore, this is the most likely pattern of collusion that is suggestive of fraud, waste, and abuse in the federal insurance program on the basis of flagged anomalous outcomes using the 150% criterion.

The most recent example of this type of nonrecursive pattern is the case in Wimbledon, North Dakota where an agent conspired with producers and adjusters to write false statements and manipulated claims to generate indemnity.[13] In this case the agent himself is a producer and generated claims for his own farming operations, as well as for other producers in the area. The agent (and his conspiring adjusters) aided several producers in the submission of false documents to receive crop insurance payments that they were not eligible to receive. In this case, all the participants in the collusion coordinated behavior nonrecursively to generate a fraudulent claim. In December 2002, the agent and his business entities were found guilty of assorted fraud and conspiracy charges.

The second best pattern of collusion on the basis of the 150% flagging criterion is the collusion with intermediary model H_{A2}, where the producer is the link to both the agent and the adjuster (agent ↔ producer ↔ adjuster). This result is again robust across the period of anal-

[13] This is the case of Duane Huber that was recently featured in the *Wall Street Journal* on May 5, 2003 (see Kilman). A press release describing some more of the details about this case can be seen at: http://www.rma.usda.gov/news/2002/12/1218huber.pdf. Other examples of this pattern of collusion can be seen in the 2002 RMA Program Compliance and Integrity Report.

ysis considered (Table 3). The producer in this case serves as the individual who initiates the collusion to undermine the integrity of the federal crop insurance program. This pattern of collusion suggests that producers may utilize both the agent and the adjuster to potentially undertake fraud and receive higher indemnity payments. This pattern of collusion makes sense because producers are the main beneficiaries of collusive behavior. Producers are the ones who would directly benefit from the collusion because they will receive the potentially higher indemnity payments from falsified claims. This pattern could mean that producers approach agents to find vulnerabilities and loopholes in the crop insurance program that the producer can exploit. Producers can then potentially exploit these vulnerabilities by separately colluding with adjusters to hide the fraud behavior.

An example of this type of collusion pattern is the "kickback" scheme uncovered by RMA (RMA 2002). This is a case in which a producer initiated an agreement with an agent in which the agent will receive kickbacks if the agent helps him get a policy that would make it easier for the producer to generate a fraudulent claim. The producer also colluded with the eventual crop loss adjuster by also promising him kickbacks from the fraudulent claim. In essence, the producer initiated two separate side-contracts with the adjuster and the agent. This result is in contrast to the RMA investigators' belief that the most prevalent pattern of collusion is where the adjuster is the one who initiates and coordinates the collusion (H_{A1}). The cart wheel pattern of collusion suggested by RMA investigators is only the fifth-best pattern of collusion overall, although it is also significant at the 1% level.

Among the doublet hypotheses, the best pattern of collusion using the 150% flagging criterion is the adjuster–producer model (H_{A5}). This is the case where only adjusters and producers explicitly collude to undermine the integrity of the federal crop insurance program. Although an agent may still be involved in this model, he is not explicitly interacting with the remaining entities to coordinate behavior and commit anomalous acts. Overall, this is the fourth-best pattern that fits the data. A good example of this pattern of collusion is a case in West Texas where a crop adjuster initiated a collusive arrangement with six producers to falsify loss appraisals and "earn" part of the additional indemnity received.[14] This fraud scheme occurred unbeknownst to the agent and insurance company. The adjuster in this case was convicted, sentenced to 24 months in prison (with 3 years of probation), and ordered to pay restitution of $685,720. Three of the six colluding producers have also been convicted and the others are still being investigated.

To see whether the results above are robust to alternative flagging criteria, we reran the log–linear analysis using a 200% threshold, a one standard deviation threshold, and a two standard deviation threshold. The results of these analyses for the period 1998–2000 are reported in Tables 4–6. The results of the log–linear analyses using alternative flagging criteria support the results reported for the mandated 150% threshold. The nonrecursive triplet is still the pattern of collusion that best fits the data for the time period under consideration. Furthermore, the ranking of the hypothesized models using the other flagging criteria are the same as the ranking using the 150% rule.

In summary, the results of the analysis here reveal that collusion among agents, adjusters, and producers potentially exists in the U.S. crop insurance program. The empirical evidence suggests that individual incentives most likely result in a pattern of collusion in which all three entities interact with each other to undermine the integrity of the federal crop insurance program. Therefore, if these three entities all collude, measures must be put in place to reduce incentives for colluding and committing fraud, waste, or abuse.

These incentives can be lessened if the probability of getting caught and the associated penalties increase. But this is easier said

[14] See http://www.rma.usda.gov/news/2001/03/010316doj.html for more details about this case. Also see the 2002 RMA Program Compliance and Integrity Report (p. 25).

Table 4. Results of the Log–Linear Analysis Using the 200% Flagging Criterion, RYs 1998–2000

	RY 1998			RY 1999			RY 2000		
Model	Deviance	*df*	Rank	Deviance	*df*	Rank	Deviance	*df*	Rank
Null	3,019.87	4		2,880.89	4		2,991.49	4	
Collusion with Intermediary									
(1) agent ↔ adjuster ↔ producer	882.22	2	3	997.67	2	3	847.37	2	3
(2) agent ↔ producer ↔ adjuster	101.26	2	2	157.22	2	2	128.32	2	2
(3) adjuster ↔ agent ↔ producer	1,793.88	2	5	1,493.82	2	5	1,804.02	2	5
Nonrecursive Triplet									
(4) triplet	4.98	1	1	10.56	1	1	5.91	1	1
Doublets									
(5) adjuster–producer	1,104.74	3	4	1,270.98	3	4	1,081.58	3	4
(6) adjuster–agent	2,797.36	3	7	2,607.58	3	7	2,757.28	3	7
(7) agent–producer	2,016.39	3	6	1,767.13	3	6	2,038.23	3	6

Notes: All results are significant at $P < 0.0001$. Statistic is Chi-square distributed -2 log likelihood. RY is reinsurance year; *df* is degrees of freedom.

than done. The investigative resources of the federal compliance agencies are already limited, which makes expanding monitoring and auditing activities that increase the probability of getting caught highly improbable. However, the results of this study can potentially help the RMA Compliance Division to more efficiently allocate their limited resources. This, in turn, may possibly increase the probability of catching entities that undermine the integrity of the U.S. crop insurance program.

The insights from the empirical results show what patterns of collusion are most likely suggestive of fraud, waste, and abuse in the crop insurance program. Therefore, in undertaking legislated data mining techniques to determine anomalous outcomes, the method for detecting the pattern of collusion most sug-

Table 5. Results of the Log–Linear Analysis Using the One Standard Deviation Flagging Criterion, RYs 1998–2000

	RY 1998			RY 1999			RY 2000		
Model	Deviance	*df*	Rank	Deviance	*df*	Rank	Deviance	*df*	Rank
Null	2,440.50	4		2,462.63	4		2,774.94	4	
Collusion with Intermediary									
(1) agent ↔ adjuster ↔ producer	882.02	2	3	983.65	2	3	982.44	2	3
(2) agent ↔ producer ↔ adjuster	33.90	2	2	26.14	2	2	72.35	2	2
(3) adjuster ↔ agent ↔ producer	1,387.86	2	5	1,348.00	2	5	1,573.49	2	5
Nonrecursive Triplet									
(4) triplet	0.18	1	1	0.01	1	1	10.10	1	1
Doublets									
(5) adjuster–producer	984.28	3	4	1,062.21	3	4	1,128.12	3	4
(6) adjuster–agent	2,338.24	3	7	2,384.07	3	7	2,629.26	3	7
(7) agent–producer	1,490.12	3	6	1,426.56	3	6	1,719.17	3	6

Notes: All results are significant at $P < 0.0001$. Statistic is Chi-square distributed -2 log likelihood. RY is reinsurance year; *df* is degrees of freedom.

Table 6. Results of the Log–Linear Analysis Using the Two Standard Deviations Flagging Criterion, RYs 1998–2000

	RY 1998			RY 1999			RY 2000		
Model	Deviance	*df*	Rank	Deviance	*df*	Rank	Deviance	*df*	Rank
Null	1,183.14	4		1,129.26	4		1,254.11	4	
Collusion with Intermediary									
(1) agent ↔ adjuster ↔ producer	453.15	2	3	431.60	2	3	453.28	2	3
(2) agent ↔ producer ↔ adjuster	9.51	2	2	21.11	2	2	7.88	2	2
(3) adjuster ↔ agent ↔ producer	684.55	2	5	648.52	2	5	771.74	2	5
Nonrecursive Triplet									
(4) triplet	0.20	1	1	4.67	1	1	1.97	1	1
Doublets									
(5) adjuster–producer	480.63	3	4	466.73	3	4	471.76	3	4
(6) adjuster–agent	1,155.67	3	7	1,094.13	3	7	1,235.62	3	7
(7) agent–producer	712.63	3	6	683.64	3	6	790.22	3	6

Notes: All results are significant at $P < 0.0001$. Statistic is Chi-square distributed −2 log likelihood. RY is reinsurance year; *df* is degrees of freedom.

gestive of fraud, waste, and abuse can be incorporated in automated data mining algorithms to better find these anomalous agents, adjusters, and producers. Instead of ad hoc allocation of investigative resources, a more refined criterion for further investigating anomalous agents, adjusters, and producers can be used, on the basis of the findings in this paper. If a particular compliance agent is tasked to look at one million records and audit policies, the methodology and results from this study can assist in better detection and prioritization of policies for investigation. Without the algorithm in this study and the evidence suggestive of the prevalence of the nonrecursive triplet pattern, compliance agents will have a hard time picking through a large database and choosing suspicious agents, adjusters, and producers that were likely colluding to generate false claims. A compliance agent can be flagging policies that are suggestive of agent–producer collusion since there is anecdotal evidence of this occurring, but given the results of this study it might be more beneficial to target and audit agents, adjusters, and producers that intend to collude nonrecursively because the data suggest that this is the most likely collusion pattern that generates anomalous outcomes. The challenge now is to develop automated data mining techniques that can recognize these anomalous patterns and be used by compliance personnel.

The private crop insurance companies can also play a role in reducing the agent's and adjuster's incentives to collude. If the agent's influence in choosing adjusters is curtailed by the insurance companies (i.e., adjusters are truly randomly assigned to agents), then possible involvement of adjusters in the collusion might also be eliminated. If private crop insurance companies truly follow the standard insurance industry guideline to randomly assign adjusters, then it would be more difficult for the agents and producers alone to commit potentially fraudulent acts. Currently, private crop insurance addresses the issue of collusion in crop insurance only by reviewing agents, adjusters, and producers involved in claims above $100,000, by undertaking rigorous reviews of agent or adjuster performance, by undertaking growing season inspections of agents and adjusters, by creating special investigative units, and use of data mining programs (Crop Insurance Industry). Even though private crop insurance companies can indeed implement many anti-fraud measures (as discussed above), an important issue to consider here is whether there are sufficient incentives for these companies to undertake these measures. As alluded to in the conceptual framework, the current structure of the SRA can lower a private insurance company's incentives to undertake anti-fraud measures. Hence, potential changes in the SRA may be needed to provide sufficient incentives for private companies to police collusion and fraudulent behavior in the federal crop insurance program.

Conclusions

There have been very limited studies about collusion behavior in insurance markets. This article is the first attempt at empirically analyzing the presence and the potential structure of collusion among agents, adjusters, and producers that is suggestive of fraud, waste, and abuse in the federal crop insurance program. The empirical analysis using flagged anomalous outcomes reveals that the most likely pattern of collusion present in the crop insurance program is where the agent, adjuster, and producer nonrecursively interact with each other to coordinate their behavior. But if an intermediary is known to initiate and coordinate the collusion, a pattern where the producer acts as the intermediary is the most likely pattern of collusion present in the data. This model is a better fit compared with the cart wheel hypothesis where adjusters act as the intermediary. Moreover, if only pairs of entities are considered, the empirical analysis indicates that adjuster–producer interaction is the most likely collusion pattern present in the data.

Although this article provides important advances to understanding potential patterns of collusion suggestive of fraud, waste, and abuse in the crop insurance program, further research is still needed. Results from the analysis reveal that the presence of certain patterns of collusion can serve as a way to better screen cases for further investigation. However, other variables or indicators must be investigated to further filter cases for human investigation. Optimal sets of indicators that best filter data is a potential area of further research. Another direction for further inquiry involves studies that develop optimal contract forms or penalty structures to help deter collusive behavior between entities in crop insurance. Given that a nonrecursive pattern may be the prevalent collusion pattern, theoretical economists can develop game-theoretic models that explore optimal contract or penalty structures to deter collusion among agents, adjusters, and producers. The published economic literature about collusion in insurance markets has usually studied contracts or penalty structures to deter collusion between two entities. A study that explores optimal contracts to deter collusion among three entities is an open question and may be an important contribution in the literature.

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Appendix

Table A1. Multiway Contingency Table of Anomalous Agent, Adjuster, and Producer Policy Counts Using the 150% Flagging Criterion, RY 1998

		Producer		
Adjuster		Anomalous	Not Anomalous	Total
Anomalous	Agent			
	Anomalous	611	269	880
	Not Anomalous	3,780	5,209	8,989
	Subtotal	4,391	5,478	9,869
Not Anomalous	Agent			
	Anomalous	1,636	2,870	4,506
	Not Anomalous	18,800	110,423	129,223
	Subtotal	20,436	113,293	133,729
Total		24,827	118,771	143,598

Note: RY is reinsurance year.

Table A2. Multiway Contingency Table of Anomalous Agent, Adjuster, and Producer Policy Counts Using the 150% Flagging Criterion, RY 1999

		Producer		
Adjuster		Anomalous	Not Anomalous	Total
Anomalous	Agent			
	Anomalous	748	298	1,046
	Not Anomalous	4,646	6,683	11,329
	Subtotal	5,394	6,981	12,375
Not Anomalous	Agent			
	Anomalous	1,904	3,260	5,164
	Not Anomalous	27,512	148,647	176,159
	Subtotal	29,416	151,907	181,323
Total		34,810	158,888	193,698

Note: RY is reinsurance year.

Table A3. Multiway Contingency Table of Anomalous Agent, Adjuster, and Producer Policy Counts Using the 150% Flagging Criterion, RY 2000

Adjuster		Producer: Anomalous	Producer: Not Anomalous	Producer: Total
Anomalous	Agent			
	Anomalous	692	280	972
	Not Anomalous	4,966	6,905	11,871
	Subtotal	5,658	7,185	12,843
Not Anomalous	Agent			
	Anomalous	1,979	3,474	5,453
	Not Anomalous	29,263	167,546	196,809
	Subtotal	31,242	171,020	202,262
Total		36,900	178,205	215,105

Note: RY is reinsurance year.