Abstract

We study how organizational form affects the level of misconduct in markets with asymmetric information and price-taking experts. Theoretical predictions show that rather than experts with strong reputations behaving more ethically, branded experts are actually less ethical in equilibrium. Similarly, more experienced experts are predicted to exhibit greater levels of misconduct. We test these predictions in the insurance sales industry and find that branded, company experts are 21 to 98% more likely to take advantage of customers, relative to small, independent experts. We also find empirical evidence that more experienced experts are significantly more likely to mislead their customers.

Keywords: Misconduct, Expert services, Asymmetric information, Credence Goods, Insurance, Ethics.

*We thank Tim Fedderson, Craig Garthwaite, Tom Hubbard, Mike Mazzeo, and Nicola Persico for their insightful comments. We are grateful to Eric Zhang for his excellent research assistance. We also thank individuals at the Texas Department of Insurance for their help. Brown: jen-brown@kellogg.northwestern.edu Minor: d-minor@kellogg.northwestern.edu
“... will people push the envelope and pitch lucrative and complicated products to clients even if they are not the simplest investments or the ones most directly aligned with the client’s goals? Absolutely. Every day, in fact.”
- Greg Smith, former executive at Goldman Sachs


Expert services firms are often found in markets with substantial asymmetric information problems—providers of technical expertise are common in the automotive, medical, engineering, and insurance industries. Experts benefit from customers trusting and buying their advice; however, experts may also face incentives that lead them to provide less than perfect recommendations. For example, a mechanic can provide a more extensive fix than warranted and a dentist can replace a filling that has not yet failed. In addition to overtreating a problem, experts can also suggest the wrong solution. For example, investment or insurance advisors can recommend products that offer customers less benefit, but provide themselves with greater revenue than the customers’ ideal products.

With these credence goods, it is difficult for a customer to determine whether the product or service is the best match for his or her needs. In extreme cases, the customer may never discover if the product was the most appropriate one—for example, the final benefit of life insurance is realized upon death. When it is difficult for a customer to discern the correct product or service, an expert who both advises and receives revenue based on his advice faces conflicting incentives. High quality advice fosters trust that may improve sales rates; yet, when taken by the customer, inappropriate advice may lead to higher revenues.

Many of the existing models of expert services allow advisors to adjust both quality and prices. In contrast, in this paper, we explore the role of organizational form in credence good markets with price-taking experts. For example, individual physicians and dentists may have limited scope to adjust prices; taxi cab drivers face regulated rates; and, in our empirical context, insurance sales agents face fixed commissions and prices. Specifically, we ask: How do price-taking experts’ company affiliations, experience and skill affect their propensity to engage in professional misconduct?

Reputation has been offered as a solution to asymmetric information problems in markets. Reputation is built through repeated positive interactions across or within customers over time (for examples, see Kreps (1990) and Tadelis (2003)). However, the nature of credence good markets means that misconduct is seldom observed. As a result, it is often not possible to build a reputation of good behavior. While reputation solves informational asymmetry in

---

1While purchasers of “experience goods” gain utility from the actual consumption of the product or service, purchasers of “credence goods” gain utility based on their beliefs about the product or service.
many markets, in our setting just the opposite happens: Branded and experienced experts—individuals we might typically expect to have built strong positive reputations—are the ones most likely to take advantage of customers.

The intuition is as follows: Since experts are price takers, their dimension of competition is their level of misconduct. For a given level of malfeasance, customers working with experts from big, branded companies fare better in expectation relative to customers using unbranded experts. For example, if a customer discovers that he has been misled by an advisor’s recommendation, he might be better indemnified by a big, branded company versus a small, independent expert. Branded experts cannot set their own prices to extract surplus from the larger expected consumer benefits; instead, they extract surplus through greater misconduct.

A similar intuition holds for individual expert reputation. The more experienced experts are more skillful at providing the most appropriate solution for customers’ needs. Hence, they can extract more rents through increased misconduct compared to less experience experts.

We test the predictions of our theoretical model using data from insurance markets. Here, we have a clear credence good setting, particularly in life insurance and annuity sales. Additionally, experts themselves acknowledge the ethical quandary of their field. In Cooper and Frank (2005), a survey of insurance agents finds that agents consistently identify three big ethical issues: failure to identify the customer’s needs and recommend products that meet those needs; false or misleading representation of products or services; and conflicts between customer benefits and opportunities for personal financial gain. Indeed, the volume of insurance lawsuits over malfeasance is not surprising. For a dramatic example, in 1999, Metropolitan Life Insurance Co. settled a $1.7 billion dispute with 7 million policyholders over allegations of deceptive sales practices. Prudential, State Farm and New York Life have also settled major lawsuits relating to their marketing practices, amounting to $410 million, $250 million, and $200 million, respectively. Other credence goods industries have witnessed similar legal battles—for example, annual medical malpractice awards totalled $4.45 billion in 2003.

For our empirical tests, we construct a rich dataset describing individual insurance agents operating in Texas. We match licensing data with company affiliations and detailed sales

---


4For details about these estimates, see Budetti and Waters (2005).
practice complaint records from the state regulator. We find that the odds of experts from big branded companies taking advantage of their customers are 21% to 98% greater than the odds for small, independent experts. We also find that more experienced agents are significantly more likely to mislead their customers.

Darby and Karni (1973) provide the foundation for the literature on credence goods. Pitchik and Schotter (1987) isolate the problem of the expert honestly suggesting a mode of treatment and provide comparative statics results comparing price and quality controls and the level of honesty. Pessendorfer and Wolinsky (2003) study the first stage of a similar problem: the need to provide incentives for the expert to expend enough effort to identify and provide a correct solution. Sulzle and Wambach (2005) explore how changing physician and patient incentives through higher coinsurance levels may (or may not) induce patients to increase physician search and encourage physicians to reduce fraud. Alger and Salanie (2006) also consider the role of the client and find that a patient’s ability to reject an expert’s recommendation creates a market failure. Emons (1997) shows that market equilibria with honest expert behavior exist when customers can infer sellers’ incentives for fraud from market data.

Customer heterogeneity may also drive the credence good problem. Fong (2005) shows that cheating arises when firms target high-valuation and high-cost customers. Feddersen and Gilligan (2001) find that third parties, namely activists, can ameliorate the credence good problem. Taylor (1995) examines multi-period contracts and warranties as another solution. Inderst and Ottaviani (2009, 2011, forthcoming) study firms trying to induce agents to provide advice to imperfectly informed customers. They find that mis-selling depends on firm asymmetries, customer awareness, and agents’ utility from giving suitable recommendations. Broadly, in their models, agents provide honest advice when firms are symmetric or there are sufficiently many aware customers in the market. Dulleck and Kerschbamer (2006) present a model that unifies the extant literature and rationalizes many of the previous theoretical findings.

Hubbard (1998) explores empirically the incentives faced by experts in automotive repair services. He finds that private firms are more likely than state inspectors to help vehicles pass emissions tests. Moreover, he finds that independent experts are more likely to provide favorable inspection reports, relative to branded “chain” shops with non-owner managers. Hubbard (2002) suggests that the possibility of many future transactions provides incentives for experts to offer more favorable advice, particularly where experts are residual claimants. Free-riding may also dampen individual experts’ incentives, as firms with more inspectors tend to help vehicles pass less frequently. Levitt and Syverson (2008) find that real estate agents invest more effort and secure a higher price for the sale of their own property, relative
to their customers’ homes. Similar to the mechanism proposed by Hubbard (2002), Levitt and Syverson argue that the absence of frequent and repeated interactions limits customers’ abilities to verify their agents’ service quality. They also find that the difference between agent-owned and non-agent-owned sale prices is increasing in the degree of asymmetric information about property values. In a very different context, Gruber and Owings (1996) find that physicians perform more cesarean-section deliveries in response to negative income shocks. Mullainathan, Noeth, and Schoar (2012) conduct a field audit study and find that financial advisors often recommend self-serving products. For more examples, see Dulleck and Kerschbamer (2006) and cites therein.

The paper proceeds as follows. In the next section, we present our theoretical model and results. Section 2 provides institutional background on the insurance industry. Our data is reviewed in Section 3 and our empirical results are presented in Section 4. Our final section discusses the implications of our findings.

1 A Model of Credence Goods Sales

In this paper, we present a model that is inspired by the unifying model in Dulleck and Kerschbamer (2006), hereafter DK. However, our model differs in important ways.

In DK, different outcomes are driven by experts offering services at different prices (e.g. mechanics choose quality and prices for auto repairs). In fact, virtually all of the aforementioned theory papers studied price-setting firms or advisors. In contrast, we consider a market where experts are price takers. In our empirical setting, insurance agents are constrained to offer products with fixed premiums and commissions. Industries with regulated prices also exhibit this feature.

We assume that a customer is made worse off by an inappropriate match, regardless of his or her level of need. Existing models have assumed that experts have only limited opportunities for misconduct—experts can provide a major repair for a minor problem, but can only provide a major repair for a major problem. These models have assumed away an expert’s flexibility to take advantage of customers that have major needs (see DK and cites therein). However, in practice, experts may provide inappropriate treatment to a variety of customer types. For example, a doctor can order excessive tests for any level of medical need. Similarly, an insurance agent can oversell life insurance coverage, thus generating greater commission at any level of customer need.

Rather than assuming that all experts work in a common institutional setting, we allow

---

5 Rebating—where an agent kicks back some of the commission to a client to adjust the effective price of a product—is illegal in most jurisdictions.
for two different organizational forms: experts may work for large, branded companies or as independent experts. This extension allows us to explore how different organizational structures support different levels of misconduct.

We assume there is some chance of “mistreatment” being discovered, resulting in a penalty against the expert. In general, previous work assumes that customers can only identify and punish experts for an under-provision of services—only a minor treatment given for a “major” problem can be discovered \textit{ex-post} by the customer.

Finally, we extend the credence good model to allow for heterogeneous expert skill, the introduction of connoisseur consumers, and the existence of a group of exogenously unscrupulous experts.\footnote{For a model of financial advisors in an experience good setting, see Bolton, Freixas, and Shapiro (2007).}

\section{1.1 Basic Model}

Consider an interaction between an expert and a customer that can result in two outcomes: the expert can recommend either an appropriate product or an inappropriate product.\footnote{The term “product” can be used interchangeably with treatment or service.} For convenience, we will use the index “\(R\)” and “\(W\)” as mnemonics for the “right” (appropriate) and “wrong” (inappropriate) products, respectively. The expert knows which product is appropriate for the customer, but the customer does not. After the expert makes his product recommendation, the customer must choose to buy or not to buy.

Suppose that \(\pi^R\) and \(\pi^W\) are the payoffs to an expert for selling the appropriate and inappropriate products, respectively, to a given customer. It follows that \(\pi^t\) is a reduced form representation of the net payoff (i.e., gross revenue minus business expenses) of selling product \(t \in \{R, W\}\), before any possible penalty for mis-selling to a customer (i.e., recommending \(W\)).

Let \(s\) be the probability that the expert recommends product \(W\) and \((1-s)\) be the probability that he recommends \(R\). Now, assume that there is some expected cost \(k(s) > 0\) for recommending \(W\), where \(k(0) = 0\) and \(\frac{\partial}{\partial s} k(s) > 0\). Thus, \(k(s)\) is a reduced form of the expected cost of mistreating customers which, in turn, reflects both the probability of detection and the magnitude of the punishment. Psychological costs associated with “doing the wrong thing” may also enter into \(k(s)\).

We assume that \(0 < \pi^R < \pi^W - k(\tilde{s})\), where \(\tilde{s} \in (0, 1)\) is defined below in Proposition 1. These inequalities imply that while it may be profitable for an expert to recommend \(W\) for some values of \(s\), it might not pay to recommend \(W\) in all cases. Moreover, if this inequality did not hold, then the expected cost for recommending \(W\) would be so high that customers...
would always buy the recommended product.\(^8\)

In our model, if an expert offers the inappropriate product and the customer does not buy it, then the expert still faces a negative payoff of \(-k(s)\). This captures the notion that experts who attempt to deceive their customers will face some probability of detection regardless of whether the customers actually buy the (inappropriate) products. For example, in the insurance industry, a customer typically receives a 10- to 30-day “free look” after paying for an annuity or life insurance product. During this period, a customer could discover that he was sold \(W\), report the agent to the regulator, and cancel the policy. This feature of our model relaxes the typical credence good model assumption that customers remain forever ignorant of the experts’ misconduct.\(^9\) In addition, the expert might incur psychological cost such as guilt for attempting to defraud his client.

Let \(b\) be the probability that the customer buys the expert’s recommended product and \((1 - b)\) be the probability that the customer rejects the expert’s recommendation. Suppose that the customer earns a net payoff of \(V^R\) from buying \(R\) and \(V^W\) from buying \(W\), where \(V^W < 0 < V^R\). If the customer decides not to buy any product, then her payoff is 0 (i.e., her normalized outside option). Note that we assume that a customer is worse off buying the wrong product than he would have been simply not buying at all. Absent this assumption, the customer would rather be mistreated with certainty than reject the expert’s advice, even knowing such advice is bad.

The model can be captured in a 2 x 2 game, where the first coordinate is the expert’s payoff and the second is the customer’s payoff:

\[
\begin{array}{c|cc}
    & \text{Buy} & \text{Don’t Buy} \\
\hline
\text{Right Product} & (\pi^R, V^R) & (0, 0) \\
\text{Wrong Product} & (\pi^W - k(s), V^W) & (-k(s), 0) \\
\end{array}
\]

1.2 Organizational Form

We enrich the model to consider two different organizational structures: large companies that employ their own experts and independent experts who form their own small firms. We describe these experts, respectively, as “company experts” and “independent experts”, indexed with \(m \in \{C, I\}\).

While we assume that the experts face similar payoffs across organizational forms \((\pi^t = \pi^t_I = \pi^t_C)\), the payoffs to customers may vary. In the following analysis, we assume that large firms have

---

\(^8\)In other words, these inequalities ensure that we have not assumed away the credence good problem.

\(^9\)In those models, an agent who is unsuccessful in selling \(W\) receives a payoff of 0—the same payoff he or she would earn from unsuccessfully marketing \(R\).
deeper pockets than small firms. That is, when an expert is found to have misled a client, a firm using company experts has more resources to compensate the customer, compared with a firm using independent experts.\footnote{For example, a class-action settlement by a large, branded insurance company gave aggrieved customers compensation ranging from $50 to tens of thousands of dollars, depending on policy size. (http://www.nytimes.com/1995/08/15/business/new-york-life-in-accord-on-class-action-settlement.html)} This reduces a customer’s expected cost of being mistreated. Let $d \in (0, 1)$ represents the large company firm’s ability to better indemnify an abused customer. While an independent firm’s customer who buys the wrong product faces $V^W < 0$, a company firm’s customer experiences only $(1 - d)V^W$.\footnote{Note that our results are equivalent if we instead assume that company firms product more benefits, denoted as $b \in (0, 1)$, when the appropriate product is purchased by the customer. In this case, the company firm customer receives $(1 + b)V^R$. This increased benefit might arise from differences in the breadth of services offered, multi-product discounts, online account access, 1-800 telephone support, or multiple service locations that large, company firms offer.} In the Appendix, we consider the role of monitoring in large firms—this extension endogenously produces differences in customer payoffs. In addition, if we allow experts to provide recommendations with a continuous set of customer valuations $V \in [V^W, V^R]$, a straightforward extension shows our predictions below still hold.

Proposition 1 compares equilibrium misconduct, buy rates and revenues across organizational structures.

**Proposition 1** In the unique equilibrium, independent experts are more ethical $s_I^* = \frac{V^R}{V^R - V^W} < s_C^*$, have less market share $b_I^* = \frac{k(s_I^*)}{\pi^R - \pi^W} < \frac{k(s_C^*)}{\pi^W - \pi^R}$, and have lower revenues, relative to company experts.

**Proof.** No pure strategy equilibrium exists. If experts always suggested $R$, then customers would always want to buy the recommended product. However, when customers always accept the recommendation, experts have an incentive to mis-sell. Alternatively, if experts always suggested $W$, then customers would never buy. Of course, then an expert should respond by offering $R$ instead of $W$.

We identify the mixed strategy equilibrium. The customer must be indifferent between buying and not buying:

\[ s_m V^W + (1 - s_m) V^R = 0 \]
\[ \implies 1 > s_m^* = \frac{V^R}{V^R - (1 - d_m) V^W} > 0 \]

where $d_C \in (0, 1)$ and $d_I = 0$. The expert must be indifferent between offering the right and
wrong product:

\[ b_m \pi^R + (1 - b) 0 = b_m \left( \pi^W - k(s_m) \right) + (1 - b_m) \left( -k(s_m) \right) \]

\[ \implies 0 < b_m^* = \frac{k(s_m^*)}{\pi^W - \pi^R} < 1. \]

This inequality is satisfied for both company and independent experts when \( \pi^R < \pi^W - k(\tilde{s}) \), where \( \tilde{s} = \frac{V_R}{V_R - (1 - dC) V_W} \). Note that this assumption on the primitives simply limits the relative magnitude of the expected penalty.

With \( d > 0 \), it follows that \( s_I^* < s_C^* \). Similarly, \( b_I^* < b_C^* \) follows from \( \frac{\partial}{\partial s} k(s) > 0 \). Finally, equilibrium revenue can be written as \( b_I^* \pi^R < b_C^* \pi^R \).

This proposition provides two sharp empirical predictions: (1) independent experts are less likely to take advantage of customers and yet (2) they have a lower market share, relative to company experts. Holding fixed the levels of misconduct across expert types, the company expert provides greater expected value to his customers because his firm has deep pockets. Since he is a price-taker and therefore cannot extract surplus through higher prices, he extracts surplus through increased misconduct—note that larger deep pockets leads to even more company expert misconduct in equilibrium.

We can also consider several comparative statics results: Unsurprisingly, we find that as the penalty for a given level of malfeasance \( k(s_m) \) increases, the customer buys more often. As the payoff \( \pi^R \) (\( \pi^W \)) for offering the right (wrong) product increases (decreases), the customer will also buy more often. As the customer’s benefit (cost) from buying \( R \) (\( W \)) increases (decreases), an expert is more likely to take advantage of his customer in equilibrium by selling \( W \). When experts can recommend either a more attractive appropriate product or a less damaging inappropriate product, the customer is more likely to buy and the expert is more likely to take advantage of the customer.

Note that, following Harsanyi’s (1973) purification theorem, the mixed strategies can be reframed as representing a heterogeneous population of experts, each with a pure strategy. In this scenario, there exists some marginal expert who sells \( W \) or \( R \) and some marginal customer type who buys from \( I \) or \( C \) or abstains.

To our knowledge, the extant literature has not explored credence goods sales across different organizational structures. In the following sections, we consider several extensions to our basic model.
1.3 Unscrupulous Experts

In this extension, we consider the case with some measure $\beta$ of inherently bad experts, where $0 < \beta < 1$. We assume that customers cannot distinguish between *exogenously* unscrupulous experts who always recommend $W$ and regular experts who may be *endogenously* bad when choosing to recommend $W$ over $R$. To study the broad impact of these unscrupulous experts, we assume that they are distributed evenly across organizational structures.

In a market with unscrupulous experts, a customer’s expected payoff is

$$ (1 - \beta)(s_m (1 - d_m) V^W + (1 - s_m)V^R) + \beta (1 - d_m) V^W = 0 $$

The customer’s payoff is now lower, which leads to a lower probability that a regular expert sells $W$ in equilibrium:

$$ s_m^* = \frac{V^R}{V^R - (1 - d_m) V^W} + \frac{\beta (1 - d_m) V^W}{(1 - \beta) V^R - (1 - d_m) V^W} $$

Informally, the regular expert must now be more honest to attract customers, and that honesty level is increasing in the measure of unscrupulous experts, $\beta$. In equilibrium, the customer is still indifferent between buying and not, so the overall incidence rate of misconduct (including misconduct by exogenously bad experts) remains the same; however, since the unscrupulous experts always recommend $W$, the distribution of malfeasance becomes more concentrated as $\beta$ increases.

As $\beta \to 1$, there exists a single point $\left( \frac{\beta}{(1-\beta)} \right) = \frac{V^R}{-(1-d_m)V^W}$ where regular experts always recommend $R$ and never mislead a customer. Beyond this point, there are too many unscrupulous experts and, since customers are better off never buying, the market fails. For intermediate values of $\beta$ (i.e., $\left( \frac{\beta}{(1-\beta)} \right) \leq \frac{V^R}{-(1-d_m)V^W}$), the presence of unscrupulous experts does not affect total consumer welfare since the incident rate over *all* experts remains the same.

The net impact of unscrupulous experts on regular sellers’ revenues depends on two opposing effects: Regular experts face a lower $k(s_m^*)$ as $s^*$ declines in response to the presence of exogenously bad experts. Thus, it is strictly profitable to offer only $W$. However, in response to the increased incentive to recommend inappropriate products, customers reduce their buy rate $b^*$ and seller revenues decline.

To see the net effect, replace $b^*$ with $\frac{k(s_m^*)}{\pi^R_{W-R}}$ in an expert’s revenue function (the LHS of expression (1)), yielding an expected payoff of

$$ k(s_m^*) \frac{\pi^R}{\pi^W - \pi^R} $$
Since $\frac{\partial \pi^*}{\partial \beta} < 0$ and $\frac{\partial}{\partial s} k(s) > 0$, revenue is decreasing in $\beta$. Therefore, regular experts earn lower revenues in the presence of more exogenously bad experts and would like to exclude them from the market.

We collect these results in our next proposition.

**Proposition 2** If $\frac{\beta}{1-\beta} \leq \frac{V_R}{-(1-d_m)V_W}$, then increasing the measure $\beta$ of unscrupulous experts reduces regular experts’ misconduct (i.e., $s_m^*$), lowers these experts’ revenues, reduces customers’ buy rate $b^*$, and leaves consumer surplus unchanged. If $\frac{\beta}{1-\beta} > \frac{V_R}{-(1-d_m)V_W}$, then too many unscrupulous experts exist and the market ceases to operate.

As can be readily shown, if some measure $G$ of always scrupulous experts were introduced instead, the opposite occurs: the regular experts become less ethical, have greater market share, and have higher revenue. Thus, regular experts hope for more “good” experts and fewer “bad” experts.

### 1.4 Connoisseur Consumers

In this section, we consider the impact of connoisseur consumers on the market equilibrium. Connoisseurs are defined as consumers who are perfectly informed about the appropriateness of the product and, therefore, only buy from an expert who recommends $R$. We assume that experts cannot distinguish a connoisseur from a regular customer—otherwise, the expert simply always suggests $R$ to such consumers and regular consumers are unaffected. Adding connoisseurs is equivalent to introducing some probability that a consumer knows the appropriate product for herself.

With a mass $\alpha$ of connoisseurs in the market, the expert’s indifference condition is

$$(1 - \alpha) b^* (\pi^R) + \alpha \pi^R = (1 - \alpha) (b (\pi^W - k(s_m)) + (1 - b) (-k(s_m))) - \alpha k(s_m)$$

This yields a buy rate for non-connoisseurs of

$$b_m^* = \frac{1}{1 - \alpha} \left( \frac{k(s_i)}{\pi^W - \pi^R} + \frac{\alpha \pi^R}{\pi^W - \pi^R} \right) > \frac{k(s_i)}{\pi^W - \pi^R}$$

Therefore, the overall market buy rate is

$$(1 - \alpha) b^* + \alpha (1 - s) = \frac{k(s_m)}{\pi^W - \pi^R} + \frac{\alpha \pi^R}{\pi^W - \pi^R} + \frac{-\alpha (1 - d_m) V^W}{V^R - (1 - d_m) V^W}$$

$$> \frac{k(s_m)}{\pi^W - \pi^R}$$
This expression suggests that when connoisseurs are present in the market, the expert has to be more honest (i.e., decrease $s$) since the penalty for dishonesty has increased—if an expert recommends $W$, then $\alpha$ consumers will reject his recommendation with certainty. However, regular consumers can free ride on the presence of connoisseurs and increase their buy rate $b^*$. Overall, an expert remains indifferent between suggesting $W$ or $R$, and thus continues to suggest $W$ at the rate $s^*$. It can be shown that an expert’s revenue is increasing in the measure $\alpha$ of connoisseurs. However, when the proportion of connoisseurs is sufficiently large, the expert switches to always recommending and selling $R$, as it is too likely he will be caught suggesting $W$ by a connoisseur. Of course, the presence of any unscrupulous experts along with high values of $\alpha$ still allows for a strictly positive level of misconduct in the market, $s^*_m = \beta$. We summarize these findings in our next proposition.

**Proposition 3** As the mass of connoisseurs $\alpha$ increases, the equilibrium buy rate of non-connoisseur consumers $b^*_m \to 1$ while expert revenues increase. The level of expert misconduct $s^*_m$ remains unchanged for lower levels of $\alpha$; when $\alpha$ is sufficiently large, $s^*_m$ decreases to $\beta$.

Note that this extension links the canonical experience and credence good models: when $\alpha = 1$, customers can perfectly assess product quality after purchase (and return a low quality product to the seller); when $\alpha = 0$, the customer never learns the true product quality.

### 1.5 Observable Differences in Expert Skill

We consider a version of the model where, on occasion, experts *inadvertently* recommend the inappropriate product.\(^{12}\) Thus, we assume that an expert makes harmful mistakes—that is, he believes that he is offering $R$, but is actually recommending $W$. Of course, this expert is also able to *choose* to recommend the inappropriate product, since that may increase his revenue at the customer’s expense. In this extension, we consider the effect of experts’ skill differences conditional on their organizational form.

Suppose that an expert is either high-skilled ($H$) or low-skilled ($L$), where skill reflects an ability to avoid making mistakes. Let $h_z$ be the probability that an expert makes an error, where $z \in \{L, H\}$.

An expert must still be indifferent between attempting to offer a good and bad product:

\[
(1 - h_z) b (\pi^R) + h_z (b (\pi^W - k(s_z))) + (1 - b) (-k(s_z)) = b (\pi^W - k(s_z)) + (1 - b) (-k(s_z))
\]

\(^{12}\)For this section, we assume that there are no unscrupulous agents (i.e., $\beta = 0$) and no connoisseur customers (i.e., $\alpha = 0$). We also assume that rates $b$ and $s$ are uniform *within* a given organizational structures. Instead, we will introduce experts who differ in terms of their skill, conditional upon their institutional home.
\[
\implies b^*_z = \frac{k(s^*_z)}{(\pi W - \pi R)}
\]

Note that this expression is the same as in the basic model; however, the level of ethical sales \(s^*_z\) will change with experts' mistakes, thus reducing \(b^*_z\):

\[
(s_z + h_z (1 - s_z))(1 - d_m) V^W + (1 - s_z) (1 - h_z)V^R = 0
\]

\[
\implies s^*_z = \frac{V^R}{V^R - (1 - d_m) V^W} + \frac{h_z}{(1 - h_z)} \left( \frac{(1 - d_m) V^W}{V^R - (1 - d_m) V^W} \right) < \frac{V^R}{V^R - (1 - d_m) V^W}
\]

This suggests that the less skilled an expert, the more ethical he must be in order to attract customers.\(^{13}\) Thus, all else equal, if an expert's experience or training is negatively correlated with the likelihood of making a mistake, then more experienced experts should have a greater rate of unethical behavior.

Similar to the revenue effect of introducing unscrupulous experts, revenues are decreasing in the rate of mistakes \(h_z\). Thus, less skilled experts are more honest, but earn lower revenues and lower customer buy rates (i.e., \(b^*_L < b^*_H\)). We summarize these findings below.\(^{14}\)

**Proposition 4** Increasing expert error rates \(h_z\) yields experts that are more ethical (i.e., \(s^*_z \downarrow\)), earn lower revenue, and face lower buy rates \(b^*_z\), relative to less error-prone experts.

**Corollary 5** If the error rate is negatively correlated with experience, more experienced experts are less ethical, have higher revenue, and face greater buy rates, relative to less experienced experts.

In summary, the model yields four main results:

1. Company experts are more likely to take advantage of customers, relative to independent experts.

2. The probability of misconduct is increasing in an expert’s level of experience.

3. When the population of expert customers is sufficiently large, expert misconduct declines. Below this threshold, increases in the number of expert customers leaves the level of expert misconduct unchanged.

4. Customers are more likely to buy from company experts, relative to independent experts.

\(^{13}\)Note that, from an expert’s perspective, the effect of mistakes is similar to the impact of introducing unscrupulous experts.

\(^{14}\)Because the expert’s skill type is commonly known, an arbitrary number of skill types leads to the same comparative statics results.
2 The Insurance Industry

2.1 Credence Goods

Insurance sales is a classic credence good market with price-taking experts. Products are complicated and multidimensional, and it is very difficult for even sophisticated consumers to identify the appropriate product for their needs. This is particularly true for life and health insurance and annuity products (LHA) where insurers impose multiple “riders” and introduce modifications to policies that may be opaque to customers. Consequently, a customer can be sold an inappropriate product, but may never become aware of the seller’s misconduct or mistake. With life insurance, the customer will never experience how well (or poorly) the policy serves his expected needs. Moreover, the insured customer and his beneficiaries may never learn whether there existed a superior product in the market at the time of purchase. In contrast, property and casualty insurance (PC) policies (i.e., auto or homeowners insurance) tend to be more understandable—both the payouts and the conditions for payouts tend to be more transparent than other insurance products. Conveniently, this feature of our empirical environment allows us to assess how the extent of the credence good qualities of a product affects misconduct.

Insurance agents cannot adjust the prices faced with individual customers—indeed, this practice called “rebating” is illegal in most jurisdictions. An insurance agent can enhance his commissions by recommending the wrong product for a customer’s given need. This increased revenue can come from simply “overselling” the level of insurance or from selling a product that also has a higher commission rate (i.e., percent received by the agent of the customer’s premium paid).

Commissions vary significantly across and within product types. For example, commissions from annuities typically range between 2 and 10% of the invested amount. Typically, commission amounts are not disclosed to customers, allowing an agent to recommend an inferior product for a larger commission. In general, the tradeoff between the benefits to the policyholder and the revenue for the seller is substantial—for example, a so-called “bonus” annuity pays the customer an additional interest rate in the first year; however, the bonus rate and the commission rate are very negatively correlated.

---

15 For example, life insurance policies can be term life, universal life, whole life, variable life and variable universal life. In addition, a myriad of “riders” exist, including terminal illness and disability waivers, long-term care provisions, and accidental death benefits. The National Association of Insurance Commissions publishes a buyers’ guide that describes some of the product complexities (http://www.naic.org/documents/consumer_guide_life.pdf).

16 Rebating is illegal in Texas (Texas Insurance Code CHAPTER 1806, Section 53).

17 Our commission rate estimates and discussion of organizational form are based on personal communication with professional insurance agents.
2.2 Organizational Forms

Insurance agents work primarily under two different organizational structures: the “company agent” model and the “independent agent” model.

Company agents are affiliated with a single insurance company and may market only approved products from that company. In practice, these product lists are quite large and there is little concern that company agents are too constrained. Companies using this organizational form may offer employment benefits packages to their agents and provide introductory training to inexperienced employees. New agents may also receive guaranteed salaries that phase out as they build up “books” of business, typically over 12 to 24 months. Finally, company agents also often have access to office space and administrative staff. Company agents may earn 50 to 70% of the gross commissions of their sales, depending on the type of insurance product. State Farm, Farmers Insurance, Allstate, Northwestern Mutual and New York Life are examples of firms using the company agent model (A.M. Best, 2011).

In contrast, independent agents are not affiliated with a single insurance company. Typically, under this organizational form, agents are responsible for all of their expenses; however, they earn 100% of the gross commissions on their sales. While independent agents are not restricted to selling insurance from any particular company, they usually cannot market products from insurance companies that use company agents—for example, an independent agent cannot market any State Farm products.

We include a list of insurance companies using company agents in the Appendix. In general, these firms have well-known, easily-recognized brand names. While company agents are associated with popular brand name companies, both company and independent agents earn roughly the same net commissions after accounting for business expenses (Carson et al., 2007).

3 Data

Our Texas insurance agent dataset was compiled from multiple public sources and consists of licensing, appointment, complaint, and market share information. Broadly, the data cover the population of agents operating in the state and characterize both organizational form and reported incidents of misconduct in Texas’s insurance industry.

\(^{18}\) Company agents may also be authorized to market selected products from other companies through agreements between their primary company and other firms.

\(^{19}\) In 2010, State Farm, AXA, Allstate and Metropolitan Life appeared in Brandz’s report on the top 8 most valuable global brands in the insurance industry (http://c1547732.cdn.cloudfiles.rackspacecloud.com/BrandZ_Top100_2010.pdf).
3.1 Agents and Organizational Form

The licensing data were acquired from the Texas Department of Insurance (TDI) and cover all agents who were licensed to sell insurance in the state of Texas as of 2010. Overall, the data describe 235,604 agents: 60,812 agents are licensed to sell PC insurance only; 135,441 agents are licensed to sell LHA only; and 39,351 agents hold licenses for both PC and LHA insurance. The licensing data include unique agent identifiers and the date on which each agent was first licensed.

To identify the organizational form under which individual agents operate, we match company and appointments data from two sources. Company-level data were acquired from A.M. Best (2011) and allow us to identify companies by marketing type, distinguishing firms that use company agents from ones that sell through independent agents. We then requested appointments data from the TDI for firms that we had identified as employing a company agent model. Appointments data list all agents designated to sell a firm’s products. Using agents’ license numbers, we match license holders to firms and, thus, can characterize individual agents’ affiliations. Through this process, we identify 59,511 individuals who work as company agents (25.3% of licensees in the state). The data also include the start dates of company agents’ appointments.

We also acquired marketshare data from the TDI, reporting the in-state premiums and marketshares of all firms operating in Texas.

3.2 Complaints

The TDI maintains a public directory of complaints against insurance companies, agents and agencies. We accessed data describing 501,553 unique complaints filed between 1996 and 2010. The directory indicates the date and nature of the complaint, the line of coverage, the license number of the subjects of the complaint, and whether the complaint was deemed “justified” or “unjustified” by the TDI.20 The nature of the complaints vary considerably, from claims disputes to accusations about unfair cancellations.

Many complaints, even those leveled at agents, relate to actions under the control of insurance companies (e.g. denial of payment and premium-related complaints). To focus on misconduct at the agent level, we narrow our analysis to a subset of complaints relating to individual agents’ sales practices. We also narrow our focus to complaints about PC and LHA sales.21 Table 1 summarizes these agent-level complaints by line of coverage and whether

\[20\) In the Appendix, we discuss the role of potential reporting bias due to differences in perceived payoffs across expert types. Given that reporting costs are low in practice, we do not expect any substantial bias in our current estimates.

\[21\) We exclude complaints relating to medicare supplements and employment insurance sales.
the complaints were justified or not. In total, we identify 23,088 accusations of marketing misconduct leveled against 13,356 individuals. Approximately 56% of those complaints were found to be justified. We match the complaints data to the population of agents licensed as of 2010 and find that 8,240 of these agents were the subject of at least one complaint.

Table 2 presents summary statistics for complaints, reported separately for company and independent agents. Complaints against insurance agents are rare events. Incident rates for both justified and unjustified complaints in PC sales are approximately three times higher than rates for LHA, consistent with the notion that LHA products have more pronounced credence good attributes than PC products. Note also that, as our theory suggests, complaint rates appear substantially lower for independent agents relative to company agents. Of course, these summary statistics do not reflect other differences, including agent experience and market share across organizational forms—we account for these factors in our next section of results.

Table 3 provides aggregate premium and marketshare statistics for Texas by organizational form. While firms using company agents hold the majority of the marketshare in PC, the opposite is true for LHA. Even accounting for the number of agents under each structure, the data suggest that firms using company agents account for more PC sales.

4 Results

The credence good model that we analyzed in Section 1 yields four main predictions. In the following section, we present empirical evidence for each prediction. In the first two sub-sections, we present strong evidence for our predictions about the difference in misconduct rates between company and independent agents and show that misconduct increases with agent experience. In the final two sub-sections, we consider prediction about connoisseurs and discuss differences in buy-rates.

---

22 The TDI dataset indicates that 122 agent-level marketing complaints were referred to other agencies for investigation; the broad descriptions of these individual complaints include “Agent mishandling”, “Excessive physical force”, and “Misrepresentation.” Because we do not know the outcomes of these investigations, we drop these complaints from the analysis.

23 In their seminal work on property rights theory, Grossman and Hart (1986) apply their model to the insurance industry. They predict that company firms will hold the majority of marketshare in LHA and the minority of marketshare in PC. Interestingly, their predictions align with the insurance industry structure in the early 1980s—65% independent firms in PC and 12% independent firms in LHA. These marketshares are the opposite of what we find using more recent data.
4.1 Prediction 1: Misconduct across organizational forms

Proposition 1 predicts that company agents are more likely to take advantage of customers, relative to independent agents.

A natural first question is simply: All else equal, are company agents more likely to have been the subject of a complaint (justified or unjustified), relative to independent agents? As suggested by Table 2, complaints against insurance agents occur very infrequently in the data—in Texas, fewer than 4% of agents have been the subject of a complaint and less than half of those complaints were considered justified by investigators. Since typical econometric techniques, including logistic regressions, may underestimate the probability of rare events (King and Zeng, 2001a), we estimate a logit model with a correction for the rare events bias.

King and Zeng (2001a) describe the intuition of the correction: while the large number of zeros in the data allow the density \((X|Y=0)\) to be estimated well, the scarcity of observations for the rare event means that \((X|Y=1)\) is estimated relatively poorly with tails that are systematically too short. That is, the max \((X|Y=0)\) can be estimated well, but the min \((X|Y=1)\) will always be above the true minimum. Figure 1, adapted from King and Zeng (2001a), illustrates the intuition for the case of a single regressor, \(X\). The vertical bars represent the actual observations when \(Y=1\) and the solid line is the true density from which those observations were drawn; there are sufficient observations to draw smooth density when \(Y=0\), shown as a dotted line. The estimate \(X^*\) such that \(X>X^*\) generates \(Y=1\) and \(X<X^*\) generates \(Y=0\) will be greater than the true threshold value.

Informally, the sparse observations in the lower tail of the \((Y=1)\) density are traded-off with the dense observations in the upper tail of the \((Y=0)\) density to minimize the error between the estimated and observed values. Zero observations are overweighted relative to ones yielding a higher estimate of \(X^*\). Thus, coefficients will be systematically attenuated and the predicted \(\Pr(Y=1)\) will be too small. For further details about the estimator, see King and Zeng (2001a,b).

We estimate the following equation:

\[
\Pr(Complaint_i = 1) = \frac{1}{1 + e^{-Q_i}}
\]

where \(\Pr(Complaint_i = 1)\) is equals 1 when agent \(i\) has been the subject of at least one TDI complaint and where

\[
Q_i = \alpha CompanyAgent_i + \beta X_i
\]

where \(CompanyAgent_i\) is equals 1 when agent \(i\) is a company agent, and matrix \(X_i\) contain

\(^{24}\)The question captures most misconduct—conditional receiving any PC complaint, only 29% of agents receive additional PC complaints; similarly, only 16% of LHA agents receive multiple complaints.
the agent-specific controls described below. Coefficient and variance estimates are then corrected using the method of King and Zeng (2001a).

Although the main thrust of our analysis is concerned with differences between organizational forms (coefficient $a$), our predictions also speak to the role of agent experience. Recall also that PC and LHA products vary in terms of the ease with which customers can understand the match between their needs and what the policy provides to them. To capture potential differences across product with differing credence good qualities, we distinguish between agents and complaints relating to PC and LHA. We include the following controls in $X_i$, reported in Table 4:

**Years since first licensed:** As a proxy for agent experience, we calculate the years since an agent was first licensed to sell insurance in Texas. If agents were licensed in other states prior to licensing by the TDI, we will underestimate their professional experience; if agents allowed their licenses to lapse in some interim periods, we will overestimate their experience.\(^{25}\)

**Out-of-state agent:** All agents who market insurance to consumers in Texas must be licensed by the TDI. We use the address on agents’ licenses to determine residency and include a dummy variable to indicate when an agent resides outside of Texas.

**Professional designation:** Insurance agents may seek certification from several professional organizations. In general, these organizations require members to complete course work and exams and participate in continuing education. We matched agents to member lists for 11 designations.\(^{26}\) In our empirical analysis, we include a dummy variable indicating whether the agent holds any professional designation. While only a small percentage of agents hold a professional designation, more LHA agents have completed certification programs relative to PC agents.

**License type:** We include a dummy variable to indicate whether an agent is licensed to sell only one type of insurance (i.e. PC or LHA). Most agents are licensed to sell only one type of insurance and slightly more sell LHA only.

Table 5 reports estimation results from equation (2) with the rare events correction. In both PC and LHA regressions, company agents are more likely to have received a complaint, justified or not. We transform our estimated coefficients into odds ratio form in Table 5. Results suggest that the odds of a company agent receiving any PC complaint is 39% higher than the odds of an independent agent receiving a complaint.\(^{27}\) Examining LHA, the odds of a company agent receiving any complaint is 98% higher than for an independent agent.

---

\(^{25}\)The date of licensing was not available for approximately 1.5% of agents (3,455 individuals) and we were forced to drop these agents from the analysis.

\(^{26}\)The designations are: CFP, ChFC, CLU, CAP, CASL, CLF, FSS, LUTCF, MSFS, MSM, and REBC.

\(^{27}\)Recall that odds are defined as $\frac{Pr(\text{complaint})}{Pr(\text{no complaint})}$.
PC and LHA company agents are substantially more likely to be the subject of a justified complaint, relative to their independent peers.

One might ask: Do firms using company agents systematically hire less honest agents? This seems unlikely given that company agent firms have established screening processes (e.g. applications, background checks, and interviews). In contrast, independent agents establish their own practices and are not subject this initial screening. Moreover, dishonest company agents who are fired are unlikely to gain employment at another company agent firm, but can readily move to independent sales. Thus, the pool of independent agents may include former company agents who were terminated due to dishonesty.

Results also suggest that the difference between organizational forms is affected by the extent of products’ credence good qualities. Namely, when comparing company and independent agents, LHA products—which require more trust from the consumer—are associated with even more misconduct.

Overall, we find strong empirical evidence of our first theoretical prediction that company experts are more likely to take advantage of customers than independent experts. However, one might be concerned that company agents’ access to resources in the event of allegations of misconduct (i.e. “deeper pockets”) might induce more customer complaints, relative to independent agents. In the following subsection, we explore this possibility.

4.1.1 Different Payoffs and Reporting Rates for Customers

Assume that, in expectation, a customer is harmed more by the misconduct of an independent expert, relative to a company expert. That is, the expected value of reporting an abuse conditional on conviction is greater for the customer of a company expert. If the cost of filing is very low, then almost every discovered abuse should be reported and we would not see any material difference in the ratio of justified to total complaints across organizational forms.28 However, if there exists some material cost of filing a complaint, then customers of company experts will report suspected misconduct more often. If company and independent experts are equally ethical, then company experts will face more reported complaints.

To illustrate, let $g_i$ be the probability that agent $i$ is guilty of misconduct and let $g_i$ be distributed uniformly between 0 and 1. Suppose that the expected payoffs to a customer of any conviction of a company or independent agent is $1,000 or $500, respectively. Let customers’ reporting costs be $100. A customer will not report an expert unless her expected net payoff from doing so is (weakly) positive. Therefore, the company agent’s customer

---

28Empirically, the reporting cost is expected to be low. Customers can go online to the TDI website and fill out a form in a matter of minutes. Insurance policies also must provide contact information for filing a complaint.
reports all cases where $g_i \geq 0.1$ and the independent agent’s customer reports all cases where $g_i \geq 0.2$.

Define $g^*$ as the threshold at which the customer chooses to report suspected misconduct. Now, the expected conviction rate given a report of the suspected impropriety is

$$\Pr(\text{conviction}|\text{reported}) = \frac{\int_1^{g^*} \Pr(\text{guilty}) \, f \, dg}{\int_1^{g^*} \frac{1}{1-g^*} \, dg} = \frac{1 + g^*}{2}$$

where $f$ is the density of $g$.

For our example above, conditional on being reported, $g^* = 0.2$ leads to a conviction rate of 60%, while $g^* = 0.1$ yields a conditional conviction rate of 55%. Thus, the company expert will have an unconditional conviction rate of $90\% \times 55\% = 49.5\%$ and the independent expert will be convicted $80\% \times 60\% = 48\%$ of the time.

More generally, we can write

$$\Pr(\text{conviction}) = \frac{1 - (g^*)^2}{2}$$

If reporting costs are low, $g^*$ will be small for both independent and expert customers. Hence, we would expect little distinguishable differences in reporting and conviction rates across company and independent experts. Further, by focusing on convictions (i.e., justified complaints) rather than all complaints, any potential difference is further minimized.

Empirically, there is also a countervailing force reducing reporting rates for company experts’ customers. Organizations using company experts often have a branch or district manager who may field complaints from disgruntled consumers and attempt to resolve the dispute before it reaches a regulator. In contrast, customers of independent experts have little recourse before contacting the regulator. As a result, in the data, we might expect observed complaint rates for company experts to represent a lower bound.

### 4.2 Prediction 2

In section 1.5, we describe our corollary 5 that more experienced agents are more likely to take advantage of customers.

Across all specifications in Table 5, an additional year of agent experience increases the odds of receiving a complaint by roughly 7%. Of course, agents with more experience have had more opportunities to receive a complaint. However, in this section, we present results suggesting that longevity alone cannot explain the estimated effect of experience.

In Table 6, we present results of a Tobit specification with complaints per licensed year as
the dependent variable to account for agent experience.\textsuperscript{29} Across all columns, the coefficients on agent experience are similar and statistically significant. In terms of magnitude, an additional year of experience results in an additional 0.01 complaints per year. In Table 2, we reported mean complaints per year of approximately 0.01—our Tobit results suggest that for an average agent, another year of experience may more than double the agent’s complaint rate.

In fact, our estimates are a lower bound on the true coefficient value for experience for two reasons. First, the longer an agent has been in business, the greater the proportion of “bad” apples in his cohort that has been weeded out through disciplinary actions, leaving agents who are more ethical on average. Since complaints against these “bad” apples are no longer included in the data, we expect our estimates of the effect of experience to be biased towards zero. Second, client attrition may also attenuate estimates of the effect of agent experience. Consider our dependent variable \( \frac{\text{complaints}}{\text{Years}} \), where \( \text{Years} \) is years of experience. Assume for now that there is no client attrition and an agent acquires 10 clients per year. In ten years, a new agent has acquired 100 clients. Suppose that the chance of complaint is 1% per client per year. This means an agent with 10 years of experience should (in expectation) receive one complaint that year. In an agent’s 20th year, he has 200 clients and should expect 2 complaints. Thus, without attrition, complaints per year does not depend on length of experience.

Now consider client attrition. Over the past 10 years, an agent with 20 years of total experience has acquired and retained the same number of clients as an agent with 10 years of total experience. However, due to attrition, the number of clients that he retained from his first 10 years is now less than his clients from the more recent decade. Thus, assuming that the chance of a complaint is still 1% per client per year, we would expect the complaints-per-year ratio of the agent with 20 years of experience to be less than the ratio of the agent with 10 years of experience. That is, we are underestimating the true effect of experience on complaints.

Given these biases, our empirical tests provide strong evidence that more experienced experts are more likely to take advantage of credence good customers.

One might worry that the most ethical company agents become independent operators after building up experience in the industry. If true, this could drive the difference in complaint rates between the organizational forms. However, on average, company agents have been licensed significantly longer than independent agents (\( p\text{-value}< 0.01 \)). Instead, one might wonder if bad agents are being detected and fired by the firms using company

\textsuperscript{29}While the Tobit results are consistent in magnitude and significance to our rare event logit analysis, the data fail strict tests of normality and homoskedasticity.
agents. Although our data do not allow us to observe this directly, this sorting would actually work against our predicted effect. That is, we would expect to observe higher complaints rates for independent agents if this organizational form included former “bad” company agents.

Although this is not an explicit component of our theory model, it is worth noting the sign and significance of our coefficient estimate for out-of-state agents. In Tables 5 and 6, these agents appear to be less likely to face complaints of misconduct for both PC and LHA. This aligns with the intuition that out-of-state agents, from whom it might be difficult to recover compensation in the event of a misdeed, must be more ethical in order to attract clients. Another simple explanation is that these out-of-state agents are being prosecuted by their domiciled state’s regulatory agency. Unfortunately, we observe only regulatory actions by the TDI. Finally, our empirical estimates provide little evidence that agents with professional designations are any less likely to have been the subject of complaints. Because these agents represent only 1% of the population of agents, we are unable to determine empirically whether these designations indicate skill or are simply attempted signals.

4.3 Prediction 3

The third prediction of the model, described by Proposition 3, is that an increase in the population of knowledgeable customers will weakly reduce agents’ misconduct. To test this prediction in our data, we include a variable representing the percentage of the population with a college degree in 25-miles of the agent. Here, we are assuming that the population’s education is correlated with the presence of consumers who are more knowledgeable about insurance products.

Using a distance algorithm, we calculated the distance between the geographic centroid of all Texas zipcodes and matched zipcodes to demographic data from the 2000 U.S. Census. After identifying all zipcodes within 25-miles of an agent’s business address, we aggregated the demographic statistics. To consider consumers’ education levels, we use the percentage of the nearby population with a college education (Associates, Bachelors or above). We do not include potential client demographics for non-resident agents because they do not have a Texas business location; as a result, non-resident agents are excluded from the analysis in Tables 7 and 8. For both resident PC and LHA agents, approximately 22% of the local population has a college degree (standard deviation of approximately 12%).

The results in Table 7 suggest that changes in the educational attainment of local populations has little influence on agent misconduct. The coefficients on customer education are negative in three of the four specifications, but fail to achieve statistically significance. Tobit
estimates of the effect of consumer education are similar in Table 8. Note that the inclusion of the education measure and the resulting exclusion of non-resident agents has little impact on the other coefficients of interest.

Recall that the theory predicts that only sufficiently high levels of consumer education will reduce misconduct—our empirical results suggest that the population of consumers in Texas may not have reached this threshold of financial consumer literacy. Note also that, holding fixed the degree of malfeasance, if more educated people are more likely to report a complaint, then complaint rates should be greater for experts working in more educated areas. This works against finding evidence showing that complaint rates fall in more educated areas.

4.4 Prediction 4

The final main prediction of the theory model is that company agents will face higher buy rates than independent agents. Since buy rate data are not available on an individual customer-agent level, we can only infer buy rates from marketshares.

Let \( n_m \) be the number of agents under organizational form \( m \). Suppose that \( r \in \mathbb{N} \) is an agent’s potential customer flow rate per year. As above, denote customers’ buy rate for organization type \( m \) by \( b_m \). For example, if \( r = 15 \) and \( b_m = 0.4 \), then an agent faces 15 potential new customers each the year, resulting in 6 new clients per year. Let \( p \in (0, 1) \) denote the persistence rate of clients, defined as the percentage of customers who remain clients into the next year (i.e. \( (1 - p) \) is the client attrition rate).

In the long run, we can express the number of clients for a given agent as

\[
totalclients = \sum_{j=0}^{t} p^j b_m r
\]

Now, assuming an average client has an annual total premium payment of \( \pi \), the total premiums per long-lived agent (i.e. as \( t \to \infty \)) is

\[
\frac{1}{n_m} \frac{b_m r}{1 - p} \pi
\]

We make three simplifying assumptions about the nature of the market: 1) both organizational forms have the same customer flow rate, \( r \); 2) both organizational forms have the same customer persistence rate, \( p \); 3) the size of premium paid by an average customer is the same across organizational forms. These assumptions are particularly strong for relatively young agents. To accommodate this challenge, we compare average agents with at least three
years of experience. In our data, conditional on three years of experience, company agents have approximately 14 years of experience on average, while independent agents average 11 years. For exposition, we assume a persistence rate of 0.9.

We compare the theoretical total premiums by organizational form

\[
\begin{align*}
\text{Company Expert} & : \sum_{j=0}^{14} 0.9^j b_C r \pi n_C \\
\text{Independent Expert} & : \sum_{j=0}^{11} 0.9^j b_I r \pi n_I
\end{align*}
\]

To inform our empirical test, we return to Table 3 reporting aggregate premium levels for both PC and LHA. Rearranging the expressions above, we find that

\[
\frac{b_C}{b_I} \approx 0.89 \frac{n_I}{n_C} \frac{\text{Total Company Expert Premiums}}{\text{Total Independent Expert Premiums}} \approx 0.89
\]

Recall that if \( \frac{b_C}{b_I} = 1 \), then customers buy from independent and company agents at the same rate. While our main theory model predicts that \( \frac{b_C}{b_I} > 1 \), we find a buy rate ratio that is slightly lower than 1. Of course, we make many assumptions in constructing this empirical comparison, and we cannot test whether our approximation is in fact different from 1.

Our main model assumes that \( k \) is endogenous, where \( k \) is a function of expert’s misconduct level \( s \). However, if \( k \) is instead exogenous, (e.g. a fixed cost regardless of \( s \)), it is straightforward to show that although company experts still commit greater misconduct than independent experts, they face the same buy rate \( b^* \) and \( \frac{b_C}{b_I} = 1 \). This aligns with our back-of-the-envelope calculation—we do not find evidence that buy rates are substantially greater for company expert customers, relative to independent expert customers.

### 4.5 Level of complaints

We can also consider the impact of organizational form, experience, and customer education on the level of complaints with an OLS regression that is conditional on an agent having received one or more complaints. These results are reported in Table 9.

Estimates suggest that, conditional on receiving at least one complaint, independent agents are more likely to have been the subject of multiple complaints—that is, while fewer independent agents have complaints, they are more likely to be repeat offenders. One plausible explanation is that there exists a distribution of propensity for agent malfeasance. As-

---

30 New agents experience a steep learning curve and often are not fully operational in their early years. For example, agents may begin as a trainee for two to three years or work as an assistant to a more experienced agent. This accounts for the difference between our estimates here and the values in Table 4.
assuming that the level of complaints increase with this propensity. Since independent agents are less likely to receive complaints, those who actually do must have a greater propensity for malfeasance on average. Hence, conditional on having a complaint filed, we expect these independent agents to have more complaints.

While there is little evidence that the presence of a professional designation is associated with greater incidence of expert malfeasance, we do find that the level of complaints is negatively related to having a designation. As previously discussed, it is not clear precisely what these designations represent—for example, they might reflect skill, signalling or other unobservable attributes. Since fewer than 1% of agents have any professional designation and 80% of agents with a complaint have received only one, we interpret this finding very cautiously.

5 Conclusion

In this paper, we explore how organizational form affects the level of misconduct in credence good markets with price-taking experts. Guided by theory, we find empirical evidence supporting the prediction that these markets operate differently than in standard asymmetric information problem settings.

In particular, rather than experts with strong reputations behaving more ethically, branded experts are actually less ethical in equilibrium. Similarly, experts who survive over time and become more skilled exhibit the greatest levels of misconduct. The intuition is as follows: in our setting, experts are price takers and thus extract surplus based on the value of their firm’s brand and their own skills through increased malfeasance. We find substantial empirical evidence that these predictions hold in the insurance industry.

Our work provides some preliminary suggestions for managing the credence good market problem. For low levels of monitoring (or whistleblowing), increases in monitoring may actually increase the level of misconduct; however, very intense monitoring will restore the market. Our theoretical and empirical findings also suggest that regulators should focus their efforts on more experienced experts—not only do these experts have more customers, they are also more likely to take advantage of their clients. Of course, in practice, high levels of costly monitoring may not be feasible.

We also present theoretical results that show that increases in the population of expert consumers—those who can better discern misconduct—have the two-fold positive effect of increasing expert revenues and, with sufficient numbers, restoring the market. This suggests that informational campaigns to educate customers could prove promising. However, our findings suggest that regulators should actually emphasize customer education over expert
monitoring. Intuitively, while monitoring only provides a “stick” in the event of bad advice, the presence of informed consumers disciplines dishonest expert behavior by limiting the gains from misconduct while rewarding honest advice with higher purchase rates. A natural or field experiment, where consumers are randomly endowed with more information specifically about a credence good, would be enlightening.
References


6 Appendix

6.1 Monitoring

In the main body of the paper, we consider company experts’ “deeper pockets.” In the following text, we show how monitoring leads to similar outcomes in equilibrium.

Suppose that there exists a monitor who observes experts’ recommendations with probability $q \in (0, 1)$, where $q = 0$ represents no oversight and $q = 1$ means that every expert recommendation is reviewed by the monitor. If the monitor observes an expert recommending $W$, then he stops the transaction and reports the expert to the regulator—that is, the consumer is indemnified for her loss $V^W$ (i.e. she receives her outside option 0) and the expert faces penalty $-k(s_m)$ and does not keep any positive payoff $\pi^W$.\footnote{Alternatively, we could assume that the penalty $k(s_m)$ is greater when misconduct is discovered by the monitor. This does not change the qualitative results, so we omit this extension for ease of exposition.} If the monitor observes an expert recommending $R$, then he does not intercede. Therefore, the expert’s payoff for suggesting $R$ is still $\pi^R$, but his payoff for recommending $W$ is now $(1 - q) \left( b_m \pi^W - k(s_m) \right) + q(-k(s_m))$.

Note this setting is similar to having connoisseur customers. However, the monitor does not purchase from the expert in the event she recommends $R$, as do connoisseur customers. Thus, connoisseur customers impose both a carrot and a stick to incentivize good conduct, whereas the monitor only imposes a stick.

With monitoring, a customer’s buy rate is higher than when $q = 0$:

$$b^* = \frac{k(s_m^*)}{(1 - q)\pi^W - \pi^R} > \frac{k(s_m^*)}{\pi^W - \pi^R}$$

The intuition is straightforward: The expert now has a lower net payoff to recommending $W$, so the customer is more tempted to follow the expert’s recommendation. As shown below, $s^*$ is larger in equilibrium, resulting in an even larger $b^*$.

Since monitoring changes customers’ payoffs, the level of $s$ will also change. In particular, though the customer’s payoff is still $V^R$ when being sold the proper product, she now receives $(1 - q)V^W < V^W$ when the inappropriate product is purchased. That is, she is saved from some of her bad recommendation purchases.

Now, $s^*$ is

$$s^* = \frac{V^R}{V^R - (1 - q)V^W} > \frac{V^R}{V^R - V^W}$$

Not only is $s^*$ now greater than without monitoring, but it is also increasing in the level of monitoring $(\frac{ds^*}{dq} > 0$ since $V^W < 0$). After some level of monitoring $q \in (0, 1)$, the expected
cost of recommending $W$ is so great that the expert only recommends $R$. This occurs when

$$(1 - q) \left( b_m \pi^W - k(s_m) \right) + q(-k(s_m)) \leq b_m \pi^R$$

which happens necessarily when $q \in \left[ \frac{\pi^W - \pi^R}{\pi^W}, 1 \right]$ since $k(s_m) \geq 0$. Define $\bar{q} = \frac{\pi^W - \pi^R}{\pi^W}$.

However, at some $q < \bar{q}$ and $k(s_m) > 0$, the buy rate will already equal 1. In particular when

$$b^* = \frac{k(s^*)}{(1 - q)\pi^W - \pi^R} = 1$$

which means the level of monitoring $q$ where the customer always buys is

$$q = \frac{\pi^W - \pi^R - k(s^*)}{\pi^W}$$  \hspace{1cm} (3)$$

It is easy to show that although $k(\cdot)$ is a function of $q$, there is a unique value of $q$ that solves (3). When $q \in (q, \bar{q})$ the customer then always buys, which means for this region of monitoring the expert now faces the problem

$$\max_s \left( (1 - q)\pi^W - k(s) \right) + (1 - s)\pi^R$$

Recall at $q = \bar{q}$, with $k(s^*)$, the above expression is zero, thus with $q \in (q, \bar{q})$, the optimal $s < s^*$ at $q \geq \bar{q}$. Since $k(0) = k'(0) = 0$, there is an interior solution. Note the optimal $s$ will now be decreasing in $q$ for $q \in (q, \bar{q})$. Finally, revenue at $q = \bar{q}$ is $\pi^R$, which means there is an initial jump in revenue as $q$ passes $\bar{q}$ but then revenue is strictly decreasing in $q$ and returns to $\pi^R$ when $q = \bar{q}$.

To illustrate these three regions of monitoring, consider a simple example with $V^R = 2$, $V^W = -2$, $\pi^R = 2$, $\pi^W = 4$, and $k(s) = s^2$.  

![Graph](image-url)
One might wonder why all firms do not monitor their experts at high levels. First, intense monitoring may be too costly. Second, in practice, it may not be possible for the firm to monitor all activities, particularly when experts have the ability to hide some of their actions from the firm. In fact, since this is a credence goods market, this suggests monitoring is far from perfect, and in practice most likely in the lower region $q < \bar{q}$. More formally, consider $q = \tilde{q} \Pr(\text{detected}|\bar{q})$, where $\tilde{q}$ is the frequency an expert’s advice is reviewed by a monitor and $\Pr(\text{detected}|\bar{q})$ is the likelihood of the monitor detecting misconduct given the reviewing of an expert’s recommendation. Thus even with $\tilde{q} = 1$, since $\Pr(\text{detected}|\bar{q})$ is expected to be low for credence good markets, $q$ should also be low.

Monitoring is similar in spirit to whistleblowing. The critical difference is that with whistleblowing, we assume that the customer does not have an improved payoff in the event of misconduct and detection. That is, whistleblowing involves the detection of bad behavior but not the indemnification of abused customers. Since customers’ payoffs are unaffected by whistleblowing, experts do not increase their level of unethical sales behavior. If instead we assume that whistleblowing improves the customer’s expected payoff through reduced downside, the result is identical to the proposition below.

Note that we could also simply have written the downside customer payoff of $V^W$ (and the upside expert payoff of $\pi^W$) as some general increasing (decreasing) function of the degree of monitoring $q$. In this case, the comparative statics of $s^*$ and $b^*$ for $q < \bar{q}$ still follow immediately. However, we would need to put structure on $V(q)$ and $\pi^W$ to ensure the existence of some level of monitoring that restores the market.

We summarize our findings in the following proposition.

**Proposition 6** With monitoring intensity $0 \leq q < \bar{q} = \frac{\pi^W - \pi^R - k(s^*_m)}{\pi^W}$, increasing the rate of monitoring $q$ increases the level of unethical sales behavior $s^*$, expert revenues, and customer buy rate $b^*$. With monitoring intensity $1 \geq q > \tilde{q}$, markets are restored: experts always suggest $R$ and make revenue $\pi^R$ while customers always buy. For intermediate levels $q \in (\tilde{q}, \bar{q})$, increased monitoring $q$ decreases both unethical sales rate $s^*$ and revenues while customers continue to always buy.
6.2 Insurance Companies Using Company Agents in Texas

Allstate Life Insurance Company
American General Life And Accident Insurance Company
American National Insurance Company
Axa Equitable Life Insurance Company
Baltimore Life Insurance Company
Beneficial Life Insurance Company
Farmers Insurance Exchange
First Acceptance Insurance Company
Guideone Mutual Insurance Company
Kansas City Life Insurance Company
Liberty Mutual Insurance Company
Metropolitan Life Insurance Company
Modern Woodmen Of America
Monumental Life Insurance Company
MONY Life Insurance Company Of America
Mutual Of Omaha Insurance Company
National Life Insurance Company
Nationwide Mutual Insurance Company
New York Life Insurance Company
Northwestern Mutual Life Insurance Company
Penn Mutual Life Insurance Company
Pennsylvania Life Insurance Company
Physicians Life Insurance Company
Provident American Life & Health Insurance Company
State Farm Life Insurance Company
Thrivent Financial For Lutherans
Western And Southern Life Insurance Company

A list of the 945 insurance companies licensed in Texas that use independent agents is available upon request.
Figure 1: Illustration of Rare Events Bias

Adapted from King and Zeng (2001).
<table>
<thead>
<tr>
<th>Nature of Complaint</th>
<th>Property and Casualty Insurance</th>
<th>Life, Health and Annuities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Justified</td>
<td>Unjustified</td>
</tr>
<tr>
<td>Agent Mishandling</td>
<td>4746</td>
<td>4541</td>
</tr>
<tr>
<td>Inappropriate Attitude</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Churning</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Commissions</td>
<td>89</td>
<td>192</td>
</tr>
<tr>
<td>Conversion</td>
<td>2981</td>
<td>127</td>
</tr>
<tr>
<td>Failure to Provide Discount</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>Improper Inducements</td>
<td>33</td>
<td>16</td>
</tr>
<tr>
<td>Marketing Ethics</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Misleading Advertising</td>
<td>74</td>
<td>51</td>
</tr>
<tr>
<td>Misrepresentation</td>
<td>340</td>
<td>131</td>
</tr>
<tr>
<td>Pressure to Take Higher Deductible Sales</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Tie-In Sales</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Twisting</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Unauthorized Acts</td>
<td>993</td>
<td>286</td>
</tr>
<tr>
<td><strong>Total Complaints</strong></td>
<td>9264</td>
<td>5358</td>
</tr>
</tbody>
</table>
Table 2: Complaints by Organizational Form

<table>
<thead>
<tr>
<th></th>
<th>Property and Casualty</th>
<th>Life, Health and Annuities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company Agents</td>
<td># of licensed agents</td>
<td>20032</td>
</tr>
<tr>
<td>(n = 59,511)</td>
<td># of agents with justified complaints</td>
<td>1124</td>
</tr>
<tr>
<td></td>
<td>% of agents with a justified complaint</td>
<td>5.611%</td>
</tr>
<tr>
<td></td>
<td># of agents with unjustified complaints</td>
<td>1451</td>
</tr>
<tr>
<td></td>
<td>% of agents with an unjustified complaint</td>
<td>7.243%</td>
</tr>
<tr>
<td></td>
<td>mean # of justified complaints per agent</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.270</td>
</tr>
<tr>
<td></td>
<td>mean # of unjustified complaints per agent</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.239</td>
</tr>
<tr>
<td></td>
<td>mean # of justified complaints per year</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>mean # of total complaints per year</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.054</td>
</tr>
<tr>
<td>Independent Agents</td>
<td># of licensed agents</td>
<td>80131</td>
</tr>
<tr>
<td>(n=176,093)</td>
<td># of agents with justified complaints</td>
<td>1501</td>
</tr>
<tr>
<td></td>
<td>% of agents with a justified complaint</td>
<td>1.873%</td>
</tr>
<tr>
<td></td>
<td># of agents with unjustified complaints</td>
<td>1542</td>
</tr>
<tr>
<td></td>
<td>% of agents with an unjustified complaint</td>
<td>1.924%</td>
</tr>
<tr>
<td></td>
<td>mean # of justified complaints per agent</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.282</td>
</tr>
<tr>
<td></td>
<td>mean # of unjustified complaints per agent</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>mean # of justified complaints per year</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>mean # of total complaints per year</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>std dev</td>
<td>0.045</td>
</tr>
</tbody>
</table>

Note: 16,835 company agents are licensed to sell both P&C and LHA; 22,516 independent agents are licensed to sell both P&C and LHA.
Table 3 - Total Premiums and Marketshares by Organizational Form

<table>
<thead>
<tr>
<th></th>
<th>Total Premiums Written (in millions $)</th>
<th>Marketshare in %</th>
<th># Agents</th>
<th>Premium per Agent (in thousands $)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Life, Health and Annuities</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Company</td>
<td>5661.39</td>
<td>11.20</td>
<td>56314</td>
<td>100.53</td>
</tr>
<tr>
<td>Independent</td>
<td>44880.97</td>
<td>88.80</td>
<td>118478</td>
<td>378.81</td>
</tr>
<tr>
<td>Total</td>
<td>50542.36</td>
<td>88.80</td>
<td>174792</td>
<td>289.16</td>
</tr>
<tr>
<td><strong>Property and Casualty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Company</td>
<td>12082.20</td>
<td>62.97</td>
<td>20032</td>
<td>603.14</td>
</tr>
<tr>
<td>Independent</td>
<td>7105.36</td>
<td>37.03</td>
<td>80131</td>
<td>88.67</td>
</tr>
<tr>
<td>Total</td>
<td>19187.56</td>
<td>100163</td>
<td>191.56</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Property and Casualty</td>
<td></td>
<td>Life, Health and Annuities</td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------</td>
<td>----------------------</td>
<td>---------------------------</td>
<td>----------------------</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev</td>
<td>Mean</td>
<td>Std. Dev</td>
</tr>
<tr>
<td>Company Agent Indicator</td>
<td>0.196</td>
<td>0.397</td>
<td>0.320</td>
<td>0.466</td>
</tr>
<tr>
<td>Agent Years Licensed</td>
<td>8.529</td>
<td>8.021</td>
<td>8.894</td>
<td>8.529</td>
</tr>
<tr>
<td>Texas Non Resident Indicator</td>
<td>0.385</td>
<td>0.487</td>
<td>0.417</td>
<td>0.493</td>
</tr>
<tr>
<td>Professional Designation Indicator</td>
<td>0.003</td>
<td>0.058</td>
<td>0.011</td>
<td>0.106</td>
</tr>
<tr>
<td>One License Type Only Indicator</td>
<td>0.616</td>
<td>0.486</td>
<td>0.780</td>
<td>0.414</td>
</tr>
<tr>
<td></td>
<td>n=98,435</td>
<td></td>
<td>n=171,476</td>
<td></td>
</tr>
</tbody>
</table>
Table 5 - Logit results for Any and Any Justified Complaints By Agent with Rare Events Correction

**Dependent variable: 1 if Agent has received any or any justified complaints, 0 otherwise**

<table>
<thead>
<tr>
<th></th>
<th>Property and Casualty</th>
<th>Life, Health and Annuities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Any Complaint</td>
<td>Any Justified Complaint</td>
</tr>
<tr>
<td>Company Agent</td>
<td>0.331***</td>
<td>1.392</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Agent Years Licensed</td>
<td>0.064***</td>
<td>1.066</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Texas Non Resident</td>
<td>-2.801***</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>(0.122)</td>
<td>(0.162)</td>
</tr>
<tr>
<td>Professional Designation</td>
<td>-0.306</td>
<td>-0.898*</td>
</tr>
<tr>
<td></td>
<td>-0.214</td>
<td>(0.736)</td>
</tr>
<tr>
<td>One License Type Only</td>
<td>-0.681***</td>
<td>-0.623***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.339***</td>
<td>-3.945***</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.049)</td>
</tr>
</tbody>
</table>

N = 98435

* p<0.05, ** p<0.01, *** p<0.001
### Table 6 - Tobit results for Total and Justified Complaints per Year by Agent

<table>
<thead>
<tr>
<th></th>
<th><strong>Property and Casualty</strong></th>
<th></th>
<th><strong>Life, Health and Annuities</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Complaints Per Year</td>
<td>Justified Complaint Per Year</td>
<td>Complaints Per Year</td>
</tr>
<tr>
<td>Company Agent</td>
<td>0.051***</td>
<td>0.025**</td>
<td>0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Agent Years Licensed</td>
<td>0.010***</td>
<td>0.010***</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Texas Non Resident</td>
<td>-0.366***</td>
<td>-0.347***</td>
<td>-0.226***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.018)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Professional Designation</td>
<td>-0.053</td>
<td>-0.131*</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.054)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>One License Type Only</td>
<td>-0.094***</td>
<td>-0.082***</td>
<td>0.097***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.632***</td>
<td>-0.739***</td>
<td>-0.807***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.016)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>N</td>
<td>98435</td>
<td>98435</td>
<td>171476</td>
</tr>
</tbody>
</table>

* p<0.05, ** p<0.01, *** p<0.001

Note: Complaints per year is calculated based on agents' years since first licensed in Texas.
**Table 7 - Logit results for Any and Any Justified Complaints By Agent with Rare Events Correctionn (in-state agents only)**

**Dependent variable: 1 if Agent has received any or any justified complaints, 0 otherwise**

<table>
<thead>
<tr>
<th></th>
<th>Property and Casualty</th>
<th>Life, Health and Annuities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Any Complaint</td>
<td>Any Justified Complaint</td>
</tr>
<tr>
<td>Company Agent</td>
<td>Coefficient</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.351***</td>
<td>1.420</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Agent Years Licensed</td>
<td>-0.186</td>
<td>0.830</td>
</tr>
<tr>
<td></td>
<td>(0.216)</td>
<td></td>
</tr>
<tr>
<td>Professional Designation</td>
<td>-0.656***</td>
<td>0.519</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td></td>
</tr>
<tr>
<td>One License Type Only</td>
<td>-0.134</td>
<td>0.875</td>
</tr>
<tr>
<td></td>
<td>(0.296)</td>
<td></td>
</tr>
<tr>
<td>Fraction college grads within 25mi.</td>
<td>-3.345***</td>
<td>-4.111***</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(1.101)</td>
</tr>
<tr>
<td>N</td>
<td>56886</td>
<td>56886</td>
</tr>
</tbody>
</table>

* p<0.05, ** p<0.01, *** p<0.001
Table 8 - Tobit results for Total and Justified Complaints per Year by Agent (in-state agent only)

<table>
<thead>
<tr>
<th></th>
<th>Property and Casualty</th>
<th>Life, Health and Annuities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Complaints Per Year</td>
<td>Justified Complaint Per Year</td>
</tr>
<tr>
<td>Company Agent</td>
<td>0.054***</td>
<td>0.028***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Agent Years Licensed</td>
<td>0.010***</td>
<td>0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Professional Designation</td>
<td>-0.033</td>
<td>-0.115*</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>One License Type Only</td>
<td>-0.092***</td>
<td>-0.078***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Fraction college grads within 25mi.</td>
<td>-0.019</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.639***</td>
<td>-0.781***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>N</td>
<td>56886</td>
<td>56886</td>
</tr>
</tbody>
</table>

* p<0.05, ** p<0.01, *** p<0.001

Note: Complaints per year is calculated based on agents' years since first licensed in Texas.
### Table 9 - Level of Complaints Conditional on Complaints>0

<table>
<thead>
<tr>
<th></th>
<th>Property and Casualty</th>
<th></th>
<th>Life, Health and Annuities</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Complaints Per Year</td>
<td>Justified</td>
<td>Complaints Per Year</td>
<td>Justified</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Complaint Per Year</td>
<td></td>
<td>Per Year</td>
</tr>
<tr>
<td>Company Agent</td>
<td>-0.0057</td>
<td>-0.0129*</td>
<td>-0.0107**</td>
<td>-0.0159**</td>
</tr>
<tr>
<td></td>
<td>(0.0043)</td>
<td>(0.0053)</td>
<td>(0.0037)</td>
<td>(0.0051)</td>
</tr>
<tr>
<td>Agent Years Licensed</td>
<td>-0.0069***</td>
<td>-0.0065***</td>
<td>-0.0071***</td>
<td>-0.0076***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0004)</td>
<td>(0.0003)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Texas Non Resident</td>
<td>-0.0367</td>
<td>-0.0461*</td>
<td>0.0406*</td>
<td>0.0139</td>
</tr>
<tr>
<td></td>
<td>(0.0197)</td>
<td>(0.0201)</td>
<td>(0.0190)</td>
<td>(0.0189)</td>
</tr>
<tr>
<td>Professional Designation</td>
<td>-0.0241*</td>
<td>-0.0283**</td>
<td>-0.0167*</td>
<td>-0.0260**</td>
</tr>
<tr>
<td></td>
<td>(0.0106)</td>
<td>(0.0107)</td>
<td>(0.0065)</td>
<td>(0.0092)</td>
</tr>
<tr>
<td>One License Type Only</td>
<td>0.0396***</td>
<td>0.0393**</td>
<td>0.0066*</td>
<td>0.0014</td>
</tr>
<tr>
<td></td>
<td>(0.0093)</td>
<td>(0.0119)</td>
<td>(0.0034)</td>
<td>(0.0057)</td>
</tr>
<tr>
<td>Fraction college grads within 25mi.</td>
<td>-0.0216</td>
<td>-0.0245</td>
<td>0.0353</td>
<td>0.0167</td>
</tr>
<tr>
<td></td>
<td>(0.0260)</td>
<td>(0.0340)</td>
<td>(0.0184)</td>
<td>(0.0289)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.2589***</td>
<td>0.2464***</td>
<td>0.2321***</td>
<td>0.2482***</td>
</tr>
<tr>
<td></td>
<td>(0.0092)</td>
<td>(0.0125)</td>
<td>(0.0087)</td>
<td>(0.0138)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.16</td>
<td>0.16</td>
<td>0.25</td>
<td>0.33</td>
</tr>
<tr>
<td>N</td>
<td>4349</td>
<td>2411</td>
<td>3499</td>
<td>1372</td>
</tr>
</tbody>
</table>

* p<0.05, ** p<0.01, *** p<0.001

Note: Complaints per year is calculated based on agents' years since first licensed in Texas.