THREE ESSAYS ON EXTENSIONS IN RISK, UNCERTAINTY, AND INSURANCE

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ABSTRACT

In the first essay, we prove existence and uniqueness of equilibrium in a rent-seeking contest given a class of heterogeneous risk-loving players. We explore the role third-order risk attitude plays in equilibrium and find that imprudence is sufficient for risk lovers to increase rent-seeking investment above the risk-neutral outcome. Moreover, we show that rent can be fully dissipated in a standard Tullock contest when there is a large number of risk-loving players.

In the second essay, we investigates the impact classic variables like medical care and lifestyle choices have on the mean, variance and skewness of a health distribution. We achieve this by positing health as output from a stochastic production process, a seemingly practical advantage over much of the deterministic literature. We leverage this unique approach to estimate how a set of explanatory variables impact the conditional moments of a health distribution. We then use these moments in a maximum entropy framework to analyze the shape impact of medical care. We find evidence of "flat of the curve" medicine but also demonstrate the higher-order benefits of additional medical care.

In the third and final essay, we investigate risk in the context of farmer and their choice of irrigation. While the benefits and utilization of crop irrigation have long been examined in agricultural economics, little attention is paid to the potential confounding relationship that may exist with other risk-management tools. Specifically, we pursue how standard crop insurance relates to irrigation. We identify irrigation as a form of self-protection, reducing the probability of crop loss due to adverse stochastic conditions. Given this, we investigate if irrigation acts as a complement to crop insurance. We test this relationship within a model of crop yields, identifying that jointly irrigated and insured lands both receive higher average yield and lead to variance and skewness effects on the overall yield distribution.

DEDICATION

To my wife, who has been in my corner from day one. Thank you for the patience, sacrifice, and support in allowing me to pursue what I love. Words fail to express my gratitude.

To my son, who has unlimited potential. I hope this is a testament to what you can achieve with discipline and hard work.

To my Lord and Savior, who has shown me grace. Thank you for all the blessings in my life and I pray you continue to guide me and my future academic pursuits.

LIST OF ABBREVIATIONS AND SYMBOLS

θ	Degree of relative risk aversion for respective utility function
ρ	Degree of constant risk aversion for respective utility function
ϕ	Probability density function of health conditional on medical input
τ	Random variable with mean 0
ϵ	Random error component of health regression equation with mean 0
β	Regression coefficient on medical care vector
γ	Regression coefficient on non-medical input vector
λ	Lagrangian multiplier on maximum entropy equation
μ	Raw moment of underlying health distribution
E	Expectation operator
$>$	Greater than
$\geq$	Greater than or equal to
$<$	Less than
$\leq$	Less than or equal to
$=$	Equal to

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CHAPTER 1

RISK LOVERS AND THE RENT-OVERINVESTMENT PUZZLE

In the rent-seeking contest, individuals, groups, or institutions compete with one another to obtain a known prize or rent. Competition often manifests itself in the expenditure of resources designed to increase the likelihood of receiving the given rent. This game demonstrates wide practical application in fields like political lobbying, sporting contests, and many more. There exists a large volume of literature on both the theory and application of rent-seeking games.[1] Within these volumes, a notable amount of research centers on testing the theoretical conclusions of rent-seeking models within controlled experiments. However, the majority of these studies suffer from a similar yet perplexing result: subjects tend to spend more in rent-seeking effort than theory would suggest for risk-neutral participants. This is what we will consider as over-investment. [46] and [72] provide thorough reviews of the experimental literature and the prevalence of over-investment. In the survey by [72], causes of this over-investment phenomenon include bounded rationality, additional utility of winning, other-regarding preferences, and probability distortion.

Within a framework of Expected Utility (EU) theory, we provide conditions under which rent over-investment can occur in equilibrium. These conditions rely on both an agent's attitude towards risk and attitude towards downside risk also known as prudence. Originally defined by [52], prudence is a precautionary savings motive whereby savings increases when future income prospects become riskier. Within the context of EU theory, prudence is equivalent to a positive third derivative of the utility function.[2] [28] use a concept of risk apportionment to show prudence as a preference over 50-50 lottery pairs without the EU

[1] See [14] or [54] for an extensive review.

[2] [60] make the initial reference to this third-order effect and name it downside risk aversion. Their description suggests that downside-risk-averse agents dislike a transfer of risk from higher to lower levels of wealth.

assumptions. In their work, prudent agents demonstrate a risk location preference, desiring a zero mean risk in a "good" state than in tandem with a "bad" state. Within this paper, we emphasize the counterpart of prudence, i.e., imprudence, and define it as a negative third derivative of utility function.

In addition to the relationship between imprudence and rent over-investment, we also find that agents' risk-lovingness may cause rent over-dissipation, i.e., the sum of all players' investment exceeds the rent. The existing theories on risk attitudes and rent-seeking deals almost exclusively in risk aversion.[3] Most studies conclude rent-seeking expenditures decline as agents become risk averse (as opposed to the risk-neutral outcome). [44] derive this result only when rent is small. Without a restriction on rent size, [16] find that risk aversion decreases rent-seeking expenditure under the assumption that utility function exhibits constant absolute risk aversion (CARA). [53] employ a more generalized model by placing no limitation on rent size or functional form. Considering only a symmetric solution with identical agents, the authors ultimate conclusion suggests ambiguity between risk aversion and rent-seeking expenditure. It is only more recently that research has addressed higher-order risk effects in these types of games. While not a rent-seeking model per se, [27] present a loss-prevention model[4] which is equivalent to a non-strategic contest, whereby, prudent agents exert less effort to avoid a loss than their risk-neutral counterparts. [81] proves, using [27]'s analogy, risk aversion decreases rent-seeking effort in a symmetric contest under the condition of prudence.

Recently, [49] complements [27]'s results by proving that risk lovers also invest in loss prevention and they will exert more effort than the risk-neutral solution if they are imprudent. Our intuition suggests that we might be able to obtain a parallel result for a rent-seeking contest; a motivation for this paper. However, to our knowledge, there is no previous literature discussing the existence of equilibrium under risk-loving preferences. There are several

[3]Recent experimental studies suggest that risk-lovingness may help explain over-bidding in auctions. See [39] and [65].

[4]Also known as the self-protection problem first studied by [29].

papers within the rent-seeking literature focusing on the characterization of a unique equilibrium. Notably, [75] demonstrate a unique equilibrium under risk neutrality, and [16] prove a similar result under risk aversion with CARA preferences. More recently, [81] shows the existence and uniqueness of a symmetric equilibrium under decreasing absolute risk aversion (DARA) as long as the rent is small enough.[5]

In Section 2, we prove that for a set of heterogeneous risk-loving players, if each player's Arrow-Pratt measure of risk aversion does not change too quickly in the relevant income domain, then a Nash equilibrium exists and it is unique. Since the risk-aversion measure is constant given a convex CARA function, $u(w) = e^{\rho w}$ with $\rho > 0$, an equilibrium always uniquely exists with this class of utility functions. Other classes of utility functions that satisfy this restriction for some initial income and rent include convex CRRA (i.e., constant relative risk aversion) functions, $u(w) = w^{\theta}$ with $\theta > 1$. Note that we neither need to assume a very small rent in the context of Taylor's approximation nor a certain kind of monotonicity of the measure of risk aversion with respect to wealth.

We compare a risk lover's rent-seeking investment in equilibrium to the risk-neutral solution in Section 3. We find that both risk lovingness and imprudence are jointly sufficient for an increase in rent-seeking investment above the risk-neutral level. This result is important especially for researchers who use experimental observations to estimate each individual's parametric utility function. As we mentioned above, over-investment is very common in the laboratory, using a concave functional form with over-investment data will only create discrepancies.[6] We focus on two simple functional forms that exhibits risk loving, convex CARA and convex CRRA, and discuss how over-investment can be explained by risk lovingness and imprudence. We also present examples of rent seeking where that the sum of all players' expenditures exceeds the rent, a phenomenon known as rent over-dissipation. Specifically, we prove that rent over-dissipation occurs when there is a large number of risk-loving players

[5] [17] conjecture that DARA players may induce a unique equilibrium. [86] also considers the DARA case without the assumption of small rent size. However, we discover a flaw in his proof that restricts the existence of equilibrium. See Appendix B for further discussion.

[6] See [1] for an example.

in a contest. To our knowledge, this is the first paper to show that rent over-dissipation can occur in a standard Tullock contest with EU maximizing players.[7]

We discuss our results and conclude in Section 4.

1.1 Existence of equilibrium

Consider the following n-player rent-seeking game with $n \geq 2$. Player i faces an initial endowment of income I_i for $i = 1, ..., n$. Players compete for an exogenous rent of a fixed size $R \leq I_i$, for all i, by choosing a level of rent-seeking investment $x_i \geq 0$. For a representative player i, the probability of winning the rent follows the logistic contest success function:

$$p_i = \frac{f_i(x_i)}{\sum_{j=1}^{n} f_j(x_j)}, \tag{1.1}$$

where f_i is player i's production function.

Assumption 1. *$f_i(0) = 0$, $f_i'(x_i) > 0$, and $f_i''(x_i) \leq 0$ for all $x_i \geq 0$ and $i = 1, 2, ..., n$.*

The assumptions above are quite intuitive and common to both the rent-seeking literature and contests in general.

If successful in winning the rent, player i receives a final wealth $I_i - x_i + R$, otherwise he will receive $I_i - x_i$. Preferences over wealth are described by a utility function u_i and each player chooses x_i to maximize his expected utility,

$$Eu_i = p_i u_i(I_i - x_i + R) + (1 - p_i) u_i(I_i - x_i). \tag{1.2}$$

Given its significance in our results, we proceed using similar methodology to that of [75] and [16]. If we let $y_i = f_i(x_i)$, $Y = \sum_{i=1}^{n} y_i$, and $Y_{-i} = Y - y_i$, the expected utility in (1.2)

[7] In a standard Tullock contest, production function is linear and prize is fixed. See [82].

can now be written as

$$Eu_i = \left(\frac{y_i}{y_i + Y_{-i}}\right) u_i(I_i - g_i(y_i) + R) + \left(\frac{Y_{-i}}{y_i + Y_{-i}}\right) u_i(I_i - g_i(y_i)), \tag{1.3}$$

where g_i is defined as f_i^{-1}. Assumption 1 implies $g_i(0) = 0$, $g_i'(y_i) > 0$, and $g_i''(y_i) \geq 0$ for all y_i. According to (1.3), player i chooses his optimal rent-seeking production y_i, corresponding to the optimal rent-seeking investment x_i, to maximize his expected utility. We can equivalently redefine this optimization problem as one where player i chooses a pair of (y_i, p_i) to maximize

$$U_i(y_i, p_i) = p_i u_i(I_i - g_i(y_i) + R) + (1 - p_i) u_i(I_i - g_i(y_i)) \tag{1.4}$$

subject to the winning probability constraint

$$p_i = \frac{y_i}{y_i + Y_{-i}} =: p(y_i | Y_{-i}). \tag{1.5}$$

Note that $p(y_i|Y_{-i})$, player i's probability of winning, is increasing and concave in y_i, and decreasing in Y_{-i}.

Now consider player i's indifference curves in the (y_i, p_i) space.[8] Let function q_i represent the probability of winning the rent such that, given y_i, player i's expected utility is equal to a constant $\bar{U}$, that is,

$$q_i(y_i|\bar{U}) := \frac{\bar{U} - u_i(I_i - g_i(y_i))}{u_i(I_i - g_i(y_i) + R) - u_i(I_i - g_i(y_i))}. \tag{1.6}$$

Given an increasing and concave constraint $p(y_i|Y_{-i})$, if player i's indifference curve $q_i(y_i|\bar{U})$ is strictly increasing and strictly convex in y_i, there will be a unique best response, y_i^*, to the sum of all other player's rent-seeking production, Y_{-i}.[9] We state the following assumptions

[8] For a graphical representation of this approach, see [83].

[9] In fact, convexity of indifference curves is not necessary for existence of player i's best response function given a concave constraint as in (1.5). For a risk averter with CARA utility functions, indifference curves are

about each player's utility function to ensure this result. We denote player i's Arrow-Pratt measure of risk aversion by $r_i(w) = -\frac{u_i''(w)}{u_i'(w)}$.

Assumption 2. *u_i is thrice differentiable with*

(i) $u_i'(w), u_i''(w) > 0$ *for all* w *and*

(ii) $r_i(w) \geq 2r_i(z)$ *for all* $w, z \in (I_i - R, I_i + R)$.

Assumption 2 (i) suggests two conditions of note. First, strictly increasing utility implies that player i's optimal investment, x_i^*, must be less than R and thus $y_i^* < f_i(R)$. Otherwise the distribution of his final wealth after investing x_i^* will be first-order stochastically dominated by the distribution when he does not participate in the contest. Since $I_i \geq R$ as assumed at the beginning of this section and $R > x_i^*$, each player's optimal investment is not constrained by his budget. Second, we can identify the relevant income domain for each player. Since $x_i^* \in [0, R)$, each player's final wealth must be less than $I_i + R$ (if he wins the rent) and greater than $I_i - R$ (if he does not win). Thus, the relevant income domain for player i is $(I_i - R, I_i + R)$.

Assumption 2 (ii) imposes that the Arrow-Pratt measure of risk aversion does not change too quickly within the relevant income domain. If we pick any pair of w and z from the interval $(I_i - R, I_i + R)$ and find that $r_i(w) \geq r_i(z)$, then $r_i(w) \geq 2r_i(z)$. On the other hand, if $r_i(w) < r_i(z)$, we will have $r_i(w) \geq 2r_i(z)$ if and only if the difference between $r_i(z)$ and $r_i(w)$, i.e., $r_i(z) - r_i(w)$, is smaller than $-r_i(z)$. Many functional forms of convex utility functions possess this property. Consider a convex CARA function with the form $u_i(w) = e^{\rho w}$ where $\rho > 0$. Note that $r_i(w) = r_i(z) = -\rho$ for all w and z so Assumption 2 (ii) always holds. Another example is a convex CRRA function with the form $u_i(w) = w^\theta$ where $\theta > 1$. Condition (ii) holds when the range of relevant income is not too large. For

concave yet [16] prove that the objective function is strictly quasiconcave and therefore a global maximium exists. In the proof of Lemma 2, we show, despite the fact that u_i is strictly convex in wealth, that Eu_i is strictly quasiconcave in y_i and player i's best response function exists.

example, if $I_i = 4$ and $R = 1$, then $r_i(w) \in (\frac{1-\theta}{3}, \frac{1-\theta}{5})$ for all $\theta > 1$ and $w \in (3, 5)$. It is not difficult to check whether a convex utility function satisfies this condition.

Lemma 1. *Suppose that Assumption 2 holds. Indifference curves $q_i(y_i|\bar{U})$ are strictly increasing and strictly convex in y_i for all $y_i \in [0, f_i(R))$.*

Proof. See Appendix A. □

We adopt the approach by [16] to show existence and uniqueness of equilibrium when all players are risk loving. First, given an aggregate production of other players Y_{-i}, we define each player's best response function $y_i^*(Y_{-i})$ which is player i's production level that maximizes (1.3). Then we derive player i's share function $s_i(Y^*)$ which is the probability that player i wins the contest as a function of total production of all players in the contest given player i's optimal decision. Thus, $Y^* = y_i^*(Y_{-i}) + Y_{-i}$.

Next, we obtain the following results regarding each player's best response $y_i^*(Y_{-i})$ and share function $s_i(Y^*)$.

Lemma 2. *Suppose that Assumptions 1 and 2 hold.*

(i) Player i's best-response function $y_i^*(Y_{-i})$ exists.

(ii) There exists a threshold

$$\kappa_i = \frac{u_i(I_i + R) - u_i(I_i)}{u_i'(I_i)g_i'(0)} \tag{1.7}$$

such that player i's best response has the following properties:

(a) $y_i^*(Y_{-i}) > 0$ for all $Y_{-i} \in [0, \kappa_i)$ and

(b) $y_i^*(Y_{-i}) = 0$ for all $Y_{-i} \geq \kappa_i$.

(iii) Each player's share function $s_i(Y^*)$ has the following properties:

(a) continuous on $Y^* > 0$,

(b) $s_i(Y^*) \to 1$ as $Y^* \to 0$,

(c) $s_i(Y^*) = 0$ for all $Y^* \geq \kappa_i$, and

(d) strictly decreasing in Y^* for all $Y^* \in (0, \kappa_i)$.

Proof. See Appendix A. □

To prove part (i) of Lemma 2, we show that, given Assumptions 1 and 2, player i's objective in (1.3) is strictly quasiconcave in y_i so there can be at most one positive stationary point. If such a point exists, it is the global maximum of player i's expected utility. Otherwise, the global maximum is at $y_i = 0$. Lemma 2 (ii) implies that, for player i, when the aggregate investment of all other players is larger than a threshold, he will no longer participate in the contest. The large degree of competition reduces the probability of winning, hence the expected marginal benefit of winning becomes prohibitively low. Consider the indifference curve that goes through the origin, i.e., $q_i(y_i|\bar{U} = u_i(I_i))$ where $u_i(I_i)$ is utility from not participating in the contest. When Y_{-i} becomes very large, the slope of the constraint $p(y_i|Y_{-i})$ at the origin will be smaller than the slope of the indifference curve $q_i(y_i|\bar{U} = u_i(I_i))$ at the same point. Thus the player chooses $y_i = 0$, a corner solution, when $Y_{-i} \geq \kappa_i$.

It follows from part (iii) of Lemma 2 that, for any n, $\sum_{i=1}^{n} s_i(Y^*)$ is strictly decreasing given $Y^* \in (0, \max\{\kappa_i\})$. Moreover, $\sum_{i=1}^{n} s_i(Y^*) \to n$ as $Y^* \to 0$ and $\sum_{i=1}^{n} s_i(Y^*) \to 0$ as $Y^* \to \max\{\kappa_i\}$. Hence there exists a unique value of $Y^* \in (0, \max\{\kappa_i\})$ such that $\sum_{i=1}^{n} s_i(Y^*) = 1$. We call such level of aggregate production the equilibrium level of aggregate production, Y^e. Therefore, player i's production in equilibrium is $y_i^e = s_i(Y^e)Y^e$. Given Lemma 2, we can state sufficient conditions for a unique equilibrium under risk-loving attitudes.

Proposition 1. *If Assumptions 1 and 2 hold, the rent-seeking game has a unique Nash equilibrium.*

1.2 Rent over-investment and over-dissipation

We now move to demonstrate the role third-order risk attitude plays in a rent-seeking contest. Following [52], we say that player i is prudent (imprudent) if $u_i'''(w) > (<)\ 0$ for all w.

We begin with an examination of a generalized model and then proceed with a more concrete example involving a standard Tullock contest. Consider again the optimization problem in equation (1.3) from the previous section. In a symmetric equilibrium (i.e., $g_i(y) = g(y)$, $u_i(w) = u(w)$, and $I_i = I$ for $i = 1, ..., n$) each player selects the same level of rent-seeking expenditure x, and thereby selecting a corresponding production y, which solves,[10]

$$\left(\frac{n-1}{n^2 y}\right)[u(I-g(y)+R)-u(I-g(y))] = \left[\left(\frac{1}{n}\right)u'(I-g(y)+R) + \left(\frac{n-1}{n}\right)u'(I-g(y))\right]g'(y) \tag{1.8}$$

Therefore the optimal production, y^*, given R and n, satisfies the following condition,

$$y^* g'(y^*) = \frac{(n-1)R}{n^2}\left[\frac{\left(\frac{1}{R}\right)\int\limits_{I-g(y^*)}^{I-g(y^*)+R} u'(w)dw}{\left(\frac{1}{n}\right)u'(I-g(y^*)+R) + \left(\frac{n-1}{n}\right)u'(I-g(y^*))}\right]. \tag{1.9}$$

Under the assumption of risk neutrality, the segment in brackets reduces to 1 and the solution easily simplifies to $\frac{(n-1)R}{n^2} = \widetilde{y}g'(\widetilde{y})$ where $\widetilde{y}$ results from the risk-neutral optimal investment $\widetilde{x}$. We now address what role third-order risk attitude plays in equilibrium.

Proposition 2. *Suppose that Assumptions 1 and 2 hold and all players are identical. If players are imprudent, then each player's rent-seeking investment in equilibrium is higher than the corresponding risk-neutral level.*

Proof. See Appendix A □

In the proof of Proposition 2, we show that the bracketed ratio in (1.9) is greater than 1 whenever $u'' > 0$ and $u''' < 0$. Since the left-hand side of (1.9) is strictly increasing in y, we can conclude that $y^* > \tilde{y}$. If we examine a two-player contest, the optimal rent-seeking

[10] This is a special case of the first-order condition for each player's maximization problem derived in (1.26) with $s_i(Y^e) = \frac{1}{n}$ for $i = 1, ..., n$.

condition in (1.9) can be written as

$$y^* g'(y^*) = \frac{R}{4} \left[\frac{\int_{I-g(y^*)}^{I-g(y^*)+R} u'(w)dw}{\left(\frac{1}{2}\right)\left[u'(I-g(y^*)+R)+u'(I-g(y^*))\right]R} \right] \tag{1.10}$$

where again, under risk neutrality, the right-hand side becomes $\frac{R}{4}$. However, we find that convexity of u is not relevant in determining the value of the right-hand side of (1.10). Specifically, negative u''' is necessary and sufficient for the bracketed ratio in (1.10) to be greater than 1 so that $y^* > \tilde{y}$.[11]

Corollary 1. *Suppose that Assumptions 1 and 2 hold and all players are identical. Under $n = 2$, each player's rent-seeking investment in equilibrium is higher than the corresponding risk-neutral level if and only if players are imprudent.*

If we consider the approach of [60] and interpret a positive third derivative of utility as a preference for a rightward skew, these results make intuitive sense. Prudent agents dislike additional rent-seeking expenditure because it lowers their income in the "bad" state (i.e., not winning the rent) and thereby skews the income distribution leftward. However, imprudent agents can tolerate a leftward skew, and therefore, spend more in rent-seeking efforts to garner the favored distribution. This intuition, however, can be somewhat ambiguous under the presence of risk lovingness.[12] The second-order and third-order effects may impact a player in opposite directions. In particular, it is impossible to conclude whether a prudent risk-lover will invest more or less in rent seeking than a risk-neutral player when $n \geq 3$. However, in a two-player game, this is possible and, more notably, imprudence is all that is needed to induce over-investment because the second-order effect does not matter. While this is quite limiting theoretically, much of the existing experimental research focuses on

[11] Consider (1.10). If we plot u' and draw a chord connecting $u'(I-g(y))$ and $u'(I-g(y)+R)$, we find that area under the chord, i.e., the denominator in the brackets, is smaller than area under u', i.e., the numerator in the brackets for any y if and only if u' is concave, i.e., $u''' < 0$, regardless of the sign of u''.

[12] See [53] for a detailed discussion. [81] only considers prudent risk-averters.

Table 1.1: Individual investment in symmetric Tullock contests with 2, 3, and 6 players given $I_i = 4$ and $R = 1$. The numbers in bold correspond to rent over-investment.

Number of players (n)	CARA $\rho = 1.5$	CARA $\rho = 3$	CRRA $\theta = 1.5$	CRRA $\theta = 3$	Risk Neutral
2	0.212	0.151	**0.251**	0.248	0.250
3	**0.239**	0.192	**0.231**	**0.239**	0.222
6	**0.204**	**0.211**	**0.145**	**0.162**	0.139

two-player contests.

For further clarification, consider a symmetric contest with a standard Tullock lottery where $f(x) = x$. In equilibrium, optimal rent-seeking investment in an n-player contest derived in (1.9) can be re-expressed as

$$x^* = \frac{(n-1)R}{n^2}\left[\frac{\left(\frac{1}{R}\right)\int\limits_{I-x^*}^{I-x^*+R} u'(w)dw}{\left(\frac{1}{n}\right)u'(I-x^*+R)+\left(\frac{n-1}{n}\right)u'(I-x^*)}\right]. \tag{1.11}$$

Table 1.1 presents a summary of optimal investment in a Tullock contest with various specifications for risk preference. We assume CARA and CRRA risk-lovers, i.e., $u(w) = e^{\rho w}$ and $u(w) = w^{\theta}$, with $\rho = 1.5, 3$ and $\theta = 1.5, 3$. We compare each agent's optimal investment to the risk-neutral level in symmetric contests given two, three, and six players. The values of individual investment greater than the risk-neutral level are in bold. In all examples initial income and rent size are $I = 4$ and $R = 1$ respectively. As suggested in Proposition 2, the CRRA agent with $\theta = 1.5$ chooses to invest more than the risk-neutral player because the former is an imprudent risk-lover. Both imprudence and risk lovingness have a positive effect on the optimal investment level. On the other hand, the CRRA agent with $\theta = 3$ and the CARA agents with both $\rho = 1.5$ and $\rho = 3$ are prudent risk-lovers.[13] When $n = 2$, as discussed above, risk-loving preference does not play a role, only prudence does. Since prudence has a negative effect on the optimal level of investment, these agents invest less than the risk-neutral player. However, as n increases, their risk lovingness outweighs prudence so

[13]See [18] and [26] for properties of prudent risk-lovers.

Table 1.2: Aggregate investment in symmetric Tullock contests with 2, 3, and 6 players given $I_i = 4$ and $R = 1$

Number of players (n)	CARA $\rho = 1.5$	CARA $\rho = 3$	CRRA $\theta = 1.5$	CRRA $\theta = 3$
2	0.424	0.302	0.502	0.496
3	0.717	0.576	0.693	0.717
6	1.224	1.266	0.870	0.972
minimum n for rent over-dissipation	5	5	20	7

they choose to invest more than the risk-neutral level. Interestingly, when there are 6 players, each CARA player invests more than 0.2 and the corresponding aggregate investment will be greater than the rent itself. See aggregate investment in equilibrium given different number of players in Table 1.2.

Proposition 3. *Suppose that Assumption 2 holds, all players are identical, and $f(x) = x$. If the number of players is large enough, the aggregate investment of all players in equilibrium will be greater than the rent.*

The above proposition can be stated without a formal proof. Using (1.7) we find that in a symmetric Tullock contest, each player has the same threshold value of κ_i which is

$$\kappa = \frac{u(I+R) - u(I)}{u'(I)}. \tag{1.12}$$

Note that $g_i'(0) = 1$ because $f_i(x_i) = x_i$ for $i = 1, ..., n$. Since each player will not participate in the contest if the total expenditures of all other players exceeds κ, then the aggregate expenditure in equilibrium, Y^e, will be smaller than κ. Using the properties of each player's share function in Lemma 2 part (ii), we find that rent over-dissipation, i.e., $Y^e > R$, may occur in equilibrium for some large n if $\kappa > R$. Specifically, we know that $s_i(Y^*)$ is strictly decreasing in Y^* and $s_i(\kappa) = 0$. If $\kappa > R$, then we can choose a large n where $\frac{1}{n} = s_i(Y^e)$ so that $Y^e \in (R, \kappa)$. Given (1.12), we find that $\kappa > R$ if and only if

$$\frac{u(I+R) - u(I)}{R} > u'(I). \tag{1.13}$$

Such an inequality holds for any strictly convex utility and hence the result in Proposition 3 is obtained.[14]

For each numerical example given in Table 2, we can calculate the minimum number of players so we obtain rent over-dissipation. If we let n^* denote the smallest n such that $\frac{1}{n} < s_i(R)$, then we see rent over-dissipation in the same contest with the number of players greater than n^*. In each column from left to right we find, $s_i(1) = 0.228, 0.211, 0.052$, and 0.151 so the value of n^* for each example can be calculated as in the last row of Table 2. Our theoretical prediction is consistent with [55]'s experiment where aggregate investment increases with number of players.

1.3 Conclusion

In this paper, we prove existence and uniqueness of equilibrium in a rent-seeking contest given a class of heterogeneous risk-loving players and demonstrate conditions under which rent over-investment is possible. In a symmetric contest, we find that imprudent risk-lovers will always spend more than their risk-neutral counterparts. This conclusion can explain, within EU framework, the above-equilibrium expenditures often found in the experimental literature. Moreover, we show that rent over-dissipation in equilibrium is possible given a set of risk-loving players. At the very least, future experiments may benefit from screening participants for the third-order risk attitude. Early work from [77] and more recent studies by [21] and [62] develop methods to identify prudence (or imprudence) within experimental settings.

[14] This result still holds in some generalized contests. If each player's production function has $f_i'(0) > 1$, then we will find $g_i'(0) < 1$ and the corresponding threshold value κ will be larger than in (1.12).

1.4 Appendix A: Proofs

1.4.1 Proof of Lemma 1

The slope of indifference curve $q_i(y_i|\bar{U})$ is given by

$$q_i'(y_i|\bar{U}) = [q_i\phi_i(I_i - g_i(y_i)) + (1 - q_i)\psi_i(I_i - g_i(y_i))]g_i'(y_i), \tag{1.14}$$

where

$$\phi_i(w) = \frac{u_i'(w + R)}{u_i(w + R) - u_i(w)} \tag{1.15}$$

and

$$\psi_i(w) = \frac{u_i'(w)}{u_i(w + R) - u_i(w)}. \tag{1.16}$$

Thus, under general conditions, the indifference curve is always upward sloping. By letting $v_i := I_i - g_i(y_i)$, we derive the second derivative of $q_i(y_i|\bar{U})$ with respect to y_i from (1.14) as

$$q_i''(y_i|\bar{U}) = [q_i\phi_i(v_i) + (1 - q_i)\psi_i(v_i)]g_i''(y_i) + [q_i\Phi_i(v_i) + (1 - q_i)\Psi_i(v_i)][g_i'(y_i)]^2, \tag{1.17}$$

where

$$\Phi_i(w) = \phi_i(w)[\phi_i(w) - \psi_i(w)] - \phi_i'(w) \tag{1.18}$$

and

$$\Psi_i(w) = \psi_i(w)[\phi_i(w) - \psi_i(w)] - \psi_i'(w). \tag{1.19}$$

The first term on the right-hand side of (1.17) is positive; however, the sign of the second term is uncertain. To guarantee that it is positive we assume

(i) $\phi_i'(w) \leq \phi_i(w)[\phi_i(w) - \psi_i(w)]$,

(ii) $\psi_i'(w) \leq \psi_i(w)[\phi_i(w) - \psi_i(w)]$,

for all $w \in (I_i - R, I_i)$. Even though Conditions (i) and (ii) above are stated in terms of ϕ_i and ψ_i instead of u_i, their intuition is quite simple. Using (1.15) and (1.16), we can write

Conditions (i) and (ii) as

$$\frac{u_i''(w+R)}{u_i'(w+R)} \leq 2\frac{u_i'(w+R)-u_i'(w)}{u_i(w+R)-u_i(w)} \tag{1.20}$$

and

$$\frac{u_i''(w)}{u_i'(w)} \leq 2\frac{u_i'(w+R)-u_i'(w)}{u_i(w+R)-u_i(w)} \tag{1.21}$$

for all $w \in (I_i - R, I_i)$ respectively. Thus both inequalities can be satisfied if

$$\frac{u_i''(w)}{u_i'(w)} \leq 2\frac{u_i''(z)}{u_i'(z)} \tag{1.22}$$

for all $w, z \in (I_i - R, I_i + R)$.

1.4.2 Proof of Lemma 2

Part (i) Given the optimization problem in (1.3), an interior solution y_i^* satisfies the first-order condition:

$$\begin{aligned} F(y_i^*) :=& \frac{Y_{-i}}{(y_i^*+Y_{-i})^2}[u_i(I_i - g_i(y_i^*)+R) - u_i(I_i - g_i(y_i^*))] \\ &- \left[\left(\frac{y_i^*}{y_i^*+Y_{-i}}\right) u_i'(I_i - g_i(y_i^*)+R) + \left(\frac{Y_{-i}}{y_i^*+Y_{-i}}\right) u_i'(I_i - g_i(y_i^*))\right] g_i'(y_i^*) = 0. \end{aligned} \tag{1.23}$$

For the equivalent constrained-optimization problem given by (1.4) and (1.5), an interior solution (y_i^*, p_i^*) satisfies the tangency condition and the constraint:

$$\frac{Y_{-i}}{(y_i^*+Y_{-i})^2} - [p_i^*\phi_i(v_i^*) + (1-p_i^*)\psi_i(v_i^*)]g_i'(y_i^*) = 0 \tag{1.24}$$

$$p_i^* - \frac{y_i^*}{y_i^*+Y_{-i}} = 0 \tag{1.25}$$

where $v_i^* = I_i - g_i(y_i^*)$ and ϕ_i and ψ_i are defined in (1.15) and (1.16) respectively. Substituting p_i^* from (1.25) into (1.24) yields

$$G(y_i^*) := \frac{Y_{-i}}{(y_i^* + Y_{-i})^2} - \left[\left(\frac{y_i^*}{y_i^* + Y_{-i}}\right)\phi_i(v_i^*) + \left(\frac{Y_{-i}}{y_i^* + Y_{-i}}\right)\psi_i(v_i^*)\right] g_i'(y_i^*) = 0. \tag{1.26}$$

Note that $G(y_i)$ is the difference between the slope of the constraint and the slope of indifference curve at $(y_i, p(y_i|Y_{-i}))$. Since the former is decreasing (in fact, strictly decreasing when $Y_{-i} > 0$) and the latter is strictly increasing (see Lemma 1), then $G(y_i)$ is strictly decreasing in y_i. If Y_{-i} is less than a threshold (derived in part (ii) below), $G(y_i) > 0$ when $y_i = 0$. Moreover, we find that $G(y_i) < 0$ when y_i is large enough. Thus there exists only one value y_i^* such that $G(y_i^*) = 0$. Next, we define

$$\Delta(y_i^*) := u_i(I_i - g_i(y_i^*) + R) - u_i(I_i - g_i(y_i^*)). \tag{1.27}$$

Since u' and u'' are strictly positive, then we know that $\Delta(y_i)$ is strictly positive and strictly decreasing in y_i. Given the definitions of $G(y_i)$ and $\Delta(y_i)$, we can write the first-order condition in (1.23) as

$$F(y_i^*) = G(y_i^*)\Delta(y_i^*) = 0. \tag{1.28}$$

The properties of $G(y_i)$ and $\Delta(y_i)$ described above imply that $F(y_i)$ is strictly decreasing for all $y_i \leq y_i^*$ and y_i^* is the only value of y_i such that the first-order condition holds. Thus we can say that $F(y_i) \left\{ \begin{array}{c} > \\ = \\ < \end{array} \right\} 0$ if and only if $y_i \left\{ \begin{array}{c} < \\ = \\ > \end{array} \right\} y_i^*$ and it follows that Eu_i is strictly quasiconcave in y_i. Since there is no budget constraint for each player's investment, the only possible corner solution would be at zero production which occurs only when Y_{-i} is so large that y_i^* satisfying the first-order condition is negative. If this is the case, then we know that there is no positive solution to the first-order condition in (1.23) because $F(y_i) < 0$ for all $y_i \geq 0$ so player i's optimal decision is setting $y_i = 0$.

Part (ii) We find the status quo level of player i's utility with no investment and no chance of winning $u_i(I_i)$. The constrained optimization problem yields an interior solution, i.e., $y^* > 0$ given Y_{-i}, whenever the slope of the indifference curve $q_i(y_i|\bar{U} = u_i(I_i))$ at $y_i = 0$ is smaller than the slope of the constraint curve $p(y_i|Y_{-i})$ at $y_i = 0$. Since $q_i'(y_i|\bar{U})$ is given by (1.14) and $p'(y_i|Y_{-i}) = \frac{Y_{-i}}{(y_i+Y_{-i})^2}$, we have $q_i'(y_i|\bar{U} = u_i(I_i)) < p'(y_i|Y_{-i})$ at $y_i = 0$ if and only if

$$\psi_i(I_i)g_i'(0) < \frac{1}{Y_{-i}}. \tag{1.29}$$

By letting $\kappa_i = \frac{1}{\psi_i(I_i)g_i'(0)}$, we find that $y^* > 0$ if and only if $Y_{-i} < \kappa_i$.

Part (iii) Define player i's share function, the probability that player i wins the contest given his optimal investment as $s_i(Y^*)$ where $Y^* = y_i^*(Y_{-i}) + Y_{-i}$. Since $y_i^*(0) > 0$, then $Y^* = 0$ is never in equilibrium and we do not need to define $s_i(0)$. Using the constraint (1.25), we rewrite the tangency condition (1.24) as

$$\frac{1 - p_i^*}{Y^*} - [p_i^*\phi_i(v_i^*) + (1 - p_i^*)\psi_i(v_i^*)]g_i'(y_i^*) = 0 \tag{1.30}$$

which can be rearranged as

$$p_i^* = \frac{[1 - \psi_i(v_i^*)g_i'(y_i^*)Y^*]}{[1 - \psi_i(v_i^*)g_i'(y_i^*)Y^*] + \phi_i(v_i^*)Y^*}. \tag{1.31}$$

Therefore, we have

$$s_i(Y^*) = \max\left\{\frac{[1 - \psi_i(v_i^*)g_i'(y_i^*)Y^*]}{[1 - \psi_i(v_i^*)g_i'(y_i^*)Y^*] + \phi_i(v_i^*)Y^*}, 0\right\}. \tag{1.32}$$

We find that s_i is a continuous function of Y^* for $Y^* > 0$ and 1 is its upper bound. In addition, as Y^* approaches 0, s_i converges to 1. From part (ii) we know that $y^* = 0$ if $Y_{-i} \geq \kappa_i$ where $\kappa_i = \frac{1}{\psi_i(I_i)g_i'(0)}$. Thus we can say that $s_i = 0$ if $Y^* \geq \kappa_i$ which is consistent with the numerator of (1.32). To show (d) we total differentiate the system of equations

(1.24) and (1.25) with respect to Y_{-i}.

$$\frac{dp_i^*}{dY_{-i}} = \frac{-\frac{Y_{-i}}{Y^{*4}} - \frac{y_i^*}{Y^{*2}}[p_i^*\phi_i(v_i^*) + (1-p_i^*)\psi_i(v_i^*)]g_i''(y_i^*) + \frac{y_i^*}{Y^{*2}}[p_i^*\phi_i'(v_i^*) + (1-p_i^*)\psi_i'(v_i^*)][g_i'(y_i^*)]^2]}{q_i''(y_i^*|u_i^*) - p''(y_i^*|Y_{-i})} \tag{1.33}$$

$$\frac{dy_i^*}{dY_{-i}} = \frac{\frac{y_i^*-Y_{-i}}{Y^{*3}} + \frac{y_i^*}{Y^{*2}}[\phi_i(v_i^*) - \psi_i(v_i^*)]g_i'(y_i^*)}{q_i''(y_i^*|u_i^*) - p''(y_i^*|Y_{-i})} \tag{1.34}$$

where u_i^* is the optimal expected utility corresponding to y_i^*. Since $q_i''(y_i^*|u_i^*) \geq 0$ and

$$p''(y_i^*|Y_{-i}) = \frac{-2Y_{-i}}{(y_i + Y_{-i})^3} < 0, \tag{1.35}$$

then the denominator of each equation is always positive. Consider the numerator of (1.33). The middle term is nonnegative because u_i is convex and g_i is concave. Thus $\frac{dp_i^*}{dY_{-i}} < 0$ if

$$\frac{y_i^*}{Y^{*2}}[p^*\phi_i'(v_i^*) + (1-p^*)\psi_i'(v_i^*)][g_i'(y_i^*)]^2 < \frac{Y_{-i}}{Y^{*4}}. \tag{1.36}$$

Substituting $g_i'(y_i)$ from (1.24) and $\frac{y_i^*}{Y^*}$ from (1.24) in (1.36) yields

$$p_i^*(1-p_i^*)[p_i^*\phi_i'(v_i^*) + (1-p_i^*)\psi_i'(v_i^*)] < [p_i^*\phi_i(v_i^*) + (1-p_i^*)\psi_i(v_i^*)]^2. \tag{1.37}$$

Conditions (i) and (ii) in the proof of Lemma 1 guarantee that (1.37) holds so $\frac{dp_i^*}{dY_{-i}} < 0$ for all $Y_{-i} \in (0, \kappa_i)$. Now consider (1.34). Substituting $q_i''(y_i^*|u_i^*)$ from (1.17) and $p''(y_i^*|Y_{-i})$ from (1.35) in (1.34) yields $\frac{dy_i^*}{dY_{-i}} > -1$. Given the definition of Y^* above, it follows that $\frac{dY^*}{dY_{-i}} = \frac{dy_i^*}{dY_{-i}} + 1$. Since $\frac{dy_i^*}{dY_{-i}} > -1$, then $\frac{dY^*}{dY_{-i}} > 0$. Given $\frac{dp_i^*}{dY_{-i}} < 0$, it follows that $\frac{ds_i}{dY^*} < 0$ for all $Y^* \in (0, \kappa_i)$.

1.4.3 Proof of Proposition 2

Using a generalization of Hermite-Hadamard's inequality given by Theorem 5.11 in [64], we have

$$\left(\frac{1}{n}\right) u'(I-x+R) + \left(\frac{n-1}{n}\right) u'(I-x) < \frac{n}{2R} \int_{I-x}^{I-x+\frac{2R}{n}} u'(w)dw \tag{1.38}$$

when $u''' < 0$. Using Steffensen's inequality given by Theorem 6.19 in [64], we find

$$\int_{I-x}^{I-x+\frac{2R}{n}} u'(w)dw \leq \frac{2}{n} \int_{I-x}^{I-x+R} u'(w)dw \tag{1.39}$$

when $u'' > 0$. Thus, (1.38) and (1.39) jointly imply

$$\left(\frac{1}{n}\right) u'(I-x+R) + \left(\frac{n-1}{n}\right) u'(I-x) < \frac{1}{R} \int_{I-x}^{I-x+R} u'(w)dw \tag{1.40}$$

and the bracketed term in (1.9) is greater than 1. Proposition 2 clearly follows.

1.5 Appendix B: A note on equilibrium in [86]

In the proof of Lemma 1 found in [86], the author attempts to confirm the convexity of an indifference curve G by examining its first partial derivative with respect to y_i:

$$\frac{\partial G_i}{\partial y_i} = \frac{g_i'(y_i)}{u_i(z_i^H) - u_i(z_i^L)} \left[u_i'(z_i^L) + \frac{\bar{U} - u_i(z_i^L)}{u_i(z_i^H) - u_i(z_i^L)} (u_i'(z_i^H) - u_i'(z_i^L)) \right] \tag{1.41}$$

where z_i^H denotes income with the rent and z_i^L is income without with all other variables being previously defined. The author incorrectly claims $u_i(z_i^H) - u_i(z_i^L)$ to be non-increasing in y_i when the difference is actually increasing in y_i under the assumption of risk aversion. Therefore we cannot conclude convex indifference curves and the existence of a unique equilibrium under DARA breaks down.

CHAPTER 2

BEYOND AVERAGE HEALTH: HIGHER MOMENTS OF THE HEALTH PRODUCTION FUNCTION

2.1 Introduction

Both the medical and academic communities alike have long tried to understand the specific factors that lead to better health, and most importantly, what marginal impact these factor may have. Within the field of economics, scholars often seek to understand this relationship using a production function . Modeled after the seminal work of [42], economists pose a set of factor inputs that, combined within a functional framework, lead to specific values of health. While there are many contributions in the theoretical understanding of this approach, this paper will focus on the empirical estimation of a health production function.

Notably, we address two concerns contained within this literature. First, a large number of studies demonstrate a potentially alarming result: the marginal impact of medical care utilization is close to zero.[1] Often coined "flat of the curve" medicine and largely attributed to the work of [35,37], this finding suggest that additional medical care has almost no significant impact on overall health status. Secondly, the classic framework used in estimating a health production function does not explicitly considered the stochastic nature of health. The pioneering work of [6] suggests that not only is there uncertainty in the realization of health but also in the impact that factors like medical care might pose.

We take a unique approach and model health as a stochastic production process. Here, an individual selects a set of deterministic, health-related inputs and is subject to a random health "shock" that, along with their chosen inputs, yield an overall level of health. These

[1] See [8], [70], [79], [74], [71], [32], [7], [33, 34], and [43] among others.

shocks are generally considered to represent uncertainty in either the incidence of illness or the effectiveness of inputs. [20] provide a concise discussion of these uncertainties and present a theoretical framework based on [42]. Empirically, we are now presented with estimating how health-related inputs affect not only the production function but also the overall distribution of health. To address this, we utilize a flexible moment approach whereby, under relatively beign assumptions and techniques, we measures the marginal impact of inputs on the conditional moments of a health distribution. Upon identifying these moments, we employ maximum entropy techniques to estimate health distributions and show visually how inputs affect their overall shapes. This is a robust strategy in that we make no ex-ante assumptions on the distribution of health.

Our approach enables us to examine "flat of the curve" medicine in a new light. Many papers attempt to criticize the low estimate on the marginal productivity of medical care citing unmeasured productivity spillovers (see [13]), endogeneity issues (see [23, 24]) or a generalization in measuring medical care (see [58]). However, to our knowledge only one paper ([70]) examines potential benefits to medical care outside of average health.[2] Given the technique discussed in the previous paragraph, we show that medical care does offer distributional benefits beyond mean health.

Our paper proceeds as follows. Section II presents the foundation for understanding a stochastic health production function and how it relates to the existing empirical literature. Section III lays out the technique to estimate the conditional moments of the underlying health distribution. Section IV describes both the data set and our empirical model. Section V presents our estimation results, discussion, and robustness checks. Section VI presents our technique in constructing a health distribution via maximum entropy and presents a collection of estimated distributions. We conclude in Section VII.

[2] [70] construct a measure examining the variability of death as based on the standard deviation of life expectancy. Our approach utilizes a much more direct, non-constructed measure for variance and can be extended to any higher moment of interest.

2.2 Stochastic Production and Output Distributions

In this section, we explore the processes that generate output distributions and how factor inputs affect the shape of these distributions. The goal is to demonstrate the link between the traditional description of deterministic health production and our stochastic specification. Given the discussion of uncertainty in health from the previous section, consider a simplified health production function $h = f(m, v)$ where m is a scalar input such as medical care and v represents the stochastic factors affecting health. We assume that consumer utility is increasing in h, health is increasing in m, and the random component is centered at zero, $E(v) = 0$. Figure 2.1 illustrates the connection between both the deterministic and stochastic approaches.

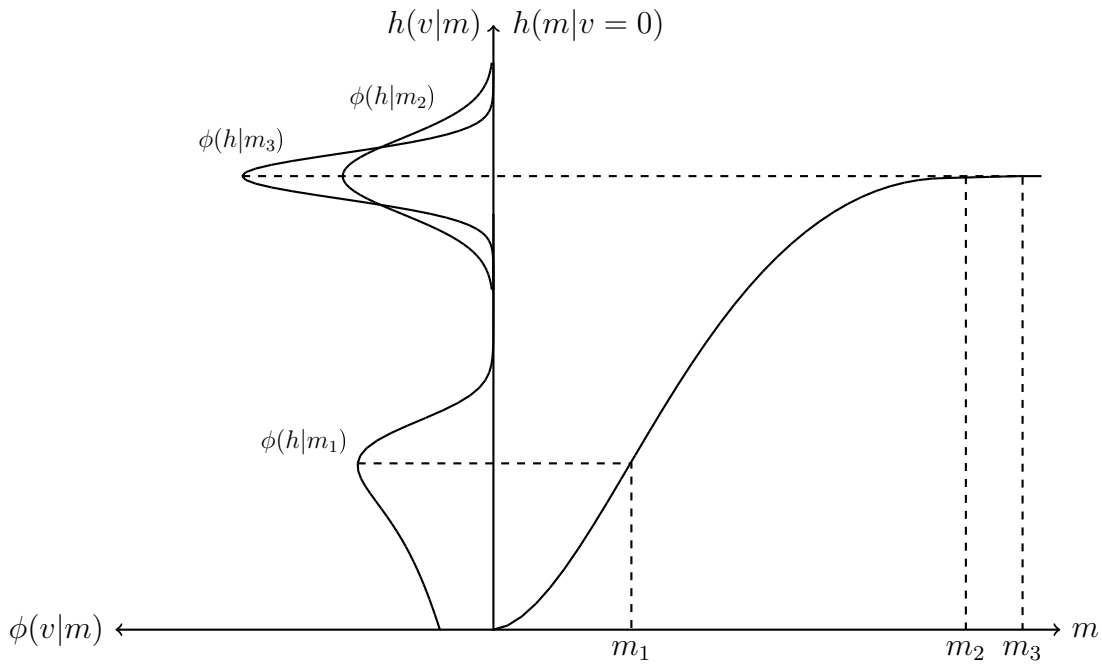
The right horizontal axis represents the nonrandom input and the vertical axis measures the corresponding health status. However, this right quadrant assumes that the stochastic component of health production takes on a specific value, mainly its average, $v = 0$. The resulting relationship is a common representation of a deterministic health production function, demonstrating both positive marginal product and decreasing marginal returns in the deterministic input.[3] Effectively, this amounts to a mean health production function, where the impact of the nonrandom input is estimated under the assumption of no uncertainty, $v = 0$.

We can demonstrate the stochastic nature of health in utilizing the left hand side of Figure 2.1. Here, the negative horizontal axis shows the probability distribution of health, ϕ, conditional on the nonrandom input, m. Estimates of a deterministic production function appear as mean values on each separate distribution. This illustrate that a wider array of possible health outcomes exists and we can speculate on the shape characteristics of each distribution.

First, consider a low-level utilization of the nonrandom input, m_1, which yields a health distribution $\phi(h|m_1)$. From the mean health production function, it is clear that increasing

[3] See [31] and [38] for a discussion of these assumptions.

Figure 2.1: Output distribution properties of a health production function with both deterministic (m) and random (v) inputs



Notes: The graphs above show the distinction between a deterministic health production function and a stochastic one. The RHS reflects the relationship between m and h in the absence of uncertainty v. The LHS shows how this uncertainty affects the distribution of health..

inputs above m_1 will lead to an increase in average health. However, consider the shape of $\phi(h|m_1)$. This distribution features a large leftward (negative) skew, indicating a higher probability of below average health outcome. An improvement in mean health from additional deterministic inputs would not recognize the potential decrease in rightward skew associated with a new conditional distribution. This potentially represents an enormous welfare improvement, assuming individuals are not risk-neutral towards health, and would otherwise go unnoticed in a deterministic evaluation.

Secondly, consider the points m_2 and m_3. The average marginal impact of the additional inputs is close to, if not equal to, zero. This phenomenon is an illustration of "flat of the curve" medicine. However, within the stochastic framework, potential welfare benefits exists in the presence of a stationary mean. As seen in the left-hand side of Figure 2.1, the increase in input utilization from m_2 to m_3 changes the health distribution from $\phi(h|m_2)$ to $\phi(h|m_3)$. Clearly, the new distribution features a lower variance in health outcome. In this context, any

risk-averse individual finds benefit in this shift and, more generally, the health distributions can be ranked via second-order stochastic dominance.

It is important to note that the distributions on the left-hand quadrant of Figure 2.1 are speculative in nature. It is the focus of this paper to determine what impact conditioning variables have on the overall shape and location of these health distributions. The sections to come provide a flexible approach to estimate these effects and suggest both medical care and other inputs have substantial benefits beyond mean shifts.

2.3 Estimation

In this section, we lay out the foundation for estimating a stochastic health production function. We do not estimate an actual health distribution per se, but allow for a set of explanatory variables to impact the conditional moments of an underlying health distribution. Consider the following adaptation of the health production function from Section II,

$$h = g(x, v) \tag{2.1}$$

where h reflects health outcome, x is a vector of exogenous inputs and v is a vector of random variables reflecting uncontrollable factors of health. As noted in the previous section, classic ordinary least squares estimation would assume particular values of the stochastic component or evaluate this component after estimation.

We instead employ an analysis often called the Linear Moment Model (LMM) and follows both the theoretical and empirical work of [4, 5].[4] Using the original specification in [4], we can estimate the probability distribution of the stochastic health production function as follows,

$$g(x, v) = f_1(x, \beta_1) + \tau \tag{2.2}$$

[4]This technique is most commonly employed modeling crop yields. See [22] and [76] for additional empirical applications.

where $f_1(x, \beta_1) \equiv E[g(x, v)]$, the mean of $g(x, v)$ and $\tau \equiv g(x, v) - f_1(x, \beta_1)$ is a random variable with $E(\tau) = 0$. This is of significance in that it links this conditional moment to our explanatory vector x. Higher moments of $g(x, v)$ are given by,

$$E\left([g(x, v) - f_1(x, \beta_1)]^k | x\right) = f_k(x, \beta_k) \tag{2.3}$$

where k indicates the particular central moment of interest. This structure allows for a common set of covariates to explain any conditional moment. As noted by [76], the linear moment approach critically relies on a correct specification of the mean equation. Any errors in modeling the mean will certainly bias all other equations and the conditional effects on higher moments. Given this, we examine the raw moments of the health distribution using the following system of equations:

$$[g(x, v)]^j = f_j(x, \beta_j) + \epsilon_j \tag{2.4}$$

where j indicates the particular raw moment of interest. While estimating raw moments may be impractical for discussion, it is of little concern given that any set of raw moments can be expressed as functions of their centered counterparts. Because of its robustness to specification error, we employ the raw moment technique in (3.5) to condition the moments of the health distribution on a traditional set of explanatory variables.

2.4 Data and Empirical Framework

This paper utilizes a balanced panel of US county-level data from 2000 through 2013. The choice of county-level data is strategic in two regards. First, it is the most disaggregated level where relatively long time series are available. National data is common to the health production literature; however, its smooths out potentially important heterogeneity.[5] One

[5] See [8], [70], and [71] among others. The same can be said, although at a diminished rate, of state-level data. See [78–80] and [66, 67] for examples.

could use individual-level data, but then would have to face issues related to the limited number of time series observations. Secondly, as noted by [9], individual-level data cannot often identify baseline or initial health. Baseline health is considered the level of health status resulting from someone's genetic predisposition and other factors. Using more aggregated data helps reduce this measurement issues in that initial health conditions may be more similar across counties than across specific groups of individuals. Hence, county-level information provides a potentially optimal trade off between both classes of data. While, on average, individual-level variability will be greater than county variability, we will effectively examine the health of a representative individual in each county.

We estimate the following model for the raw moments of health,

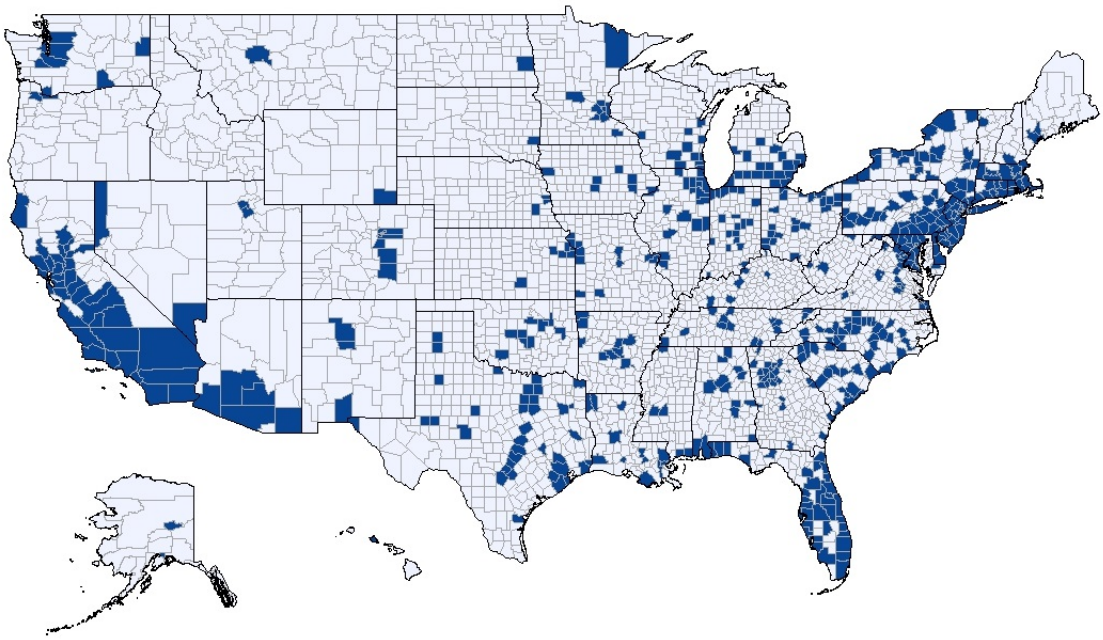
$$y_{it}^{j} = \alpha_{ij} + \rho_{tj} + \beta_j M_{it} + \gamma_j X_{it} + \lambda_j Z_{it} + \delta_j W_{it} + \epsilon_{it} \tag{2.5}$$

where the dependent variable y_{it}^{j} is the jth power of crude mortality rates y_{it} for county i in period t, α_{ij} is a county-by-equation fixed effect, ρ_{tj} is a year-by-equation fixed effect, M is a vector measuring medical care utilization, X is a matrix of demographic characteristics, Z is a matrix of lifestyle choice variables, and W is a matrix of non-medical inputs. The inclusion of both county and time fixed effects is common to the literature. The county fixed effect captures the impact of unobserved heterogeneity, which in this context, effectively measures baseline health and potential sociological characteristics that affect mortality. The time fixed effect intends to estimate changes in medical technology (see [8] for discussion). The following paragraphs present a detailed description of each data category. Variable definitions and descriptive statistics are reported in Table 2.1.

2.4.1 Crude mortality rate

The crude death rate measures the total number of deaths from all causes per 100,000 people in a calendar year. There is common agreement that health features both a length

Figure 2.2: Counties in Sample from 2000-2013



Notes: The dataset consists of 7,840 observation from 560 counties during the years 2000-2013. Counties highlight in blue are featured in the sample.

of and quality of life component.[6] To that extent, we can consider this paper to study the duration of health (life) dimension. Data is collected by the National Center for Health Statistics (NCHS) at the Centers for Disease Control and Prevention (CDC).[7]

2.4.2 Medical care utilization

Our measure of medical care utilization is the number of active medical doctors per 100,000 in the county population. Many aggregate studies utilize total spending on medical care as a control variable.[8] However, these numbers are often plagued by measurement errors resulting from area price differentials and cross-boundary medical consumption. Our variable, based on the approach by [56], potentially avoids these issues.[9] Data on active

[6]Many papers utilize a quality of health measurement often based on self-reported data. However, [10] outline the growing separation between self-reported health and clinically measured health.

[7]Counties with low death counts (less than 20) or classified as "unreliable" (see CDC for detailed description) are excluded from the sample. Additional information on source and collection can be found at http://wonder.cdc.gov/wonder/help/cmf.html.

[8]See [71], [78–80], [8], among others.

[9]A natural suspicion of endogeneity may result in our choice of medical care utilization that will be addressed in Section V.

medical doctors comes from the American Medical Association Physician Masterfiles accessed via the Area Health Resources File (AHRF) from the U.S. Department of Health and Human Service.

2.4.3 Demographic characteristics

We choose to include covariates on three demographic areas: age, gender and race. It should be intuitive that mortality rates are directly dependent on the age profile of a particular county. We include the percentage of a county's population 65 and older as a control for this effect. Further, the percentage of a county's population that is female or black are also included for control. Data on all demographic characteristics come from the decennial census and the American Community Survey (ACS).

2.4.4 Lifestyle choices

There exists a bevy of literature on the relation between lifestyle choices and health.[10] Here we use a unique set of observations on county-level prevalence of alcohol consumption, smoking and obesity. Data on these measures are extracted from the Behavioral Risk Factor Surveillance System (BRFSS), an ongoing, monthly, state-based telephone survey of the adult population conducted by the CDC. In some cases, county-level estimates are then provided by the Institute for Health Metrics and Evaluation (IHME) using small area estimation models described in [25] and the references there within.[11]

The percentage of county population who smokes measures any tobacco use over the previous 12 months. The percentage of county population engaged in excessive drinking encompasses two categories from the BRFSS. It includes any individual who binge drinks (consuming more than four drinks for women or five drinks for men on a single occasion) or heavily drinks (consuming, on average, more than one drink per day for women or two drinks per day for men). Finally, the percentage of the population obese includes any individual

[10] See [19], [78–80], [15], and [51].

[11] This includes about 65 percent of the observations on cigarette and alcohol consumption.

Table 2.1: Variable List, Descriptions, and Descriptive Statistics

Variable	Description	Mean	St. Dev.	Min	Max
Crude death rate	Deaths per 100,000 in population	822.01	208.93	265.70	1,691.80
Active doctors	Active medical doctors per 100,000 in population	26.55	20.20	1.07	229.25
Percent female	Share of population female	50.85	1.10	41.70	54.30
Percent black	Share of population black	12.94	12.50	1.00	70.30
Percent ≥ 65	Share of population over 65	12.98	3.73	4.60	36.90
Percent obese	Age-adjusted share of population obese	27.29	4.13	13.42	41.40
Percent smoke	Share of population who smoke	22.08	4.29	7.00	33.40
Percent ex. drink	Share of population engaged in excessive drinking	24.31	5.31	7.00	44.20
Median income	Median income in 2010 dollars	52,362.19	13,579.63	27,159	119,525
Percent bachelors	Share of population with Bachelor's degree	28.18	9.87	9.90	74.30

with a body mass index greater than or equal to 30.[12]

2.4.5 Non-medical inputs

We include within this group control variables for both education and income. Data on all non-medical inputs come from the decennial census and the American Community Survey (ACS). The role education plays in the production of health is an ongoing topic of active research.[13] We include the fraction of county population with a Bachelor's degree. Also, notably research suggests income plays a significant role in the production of health.[14] To that extent, we include median income as a control.

[12]Body mass index is $\left(\frac{weight[kg]}{height[m]}\right)^2$ and derived from self-report height and weight.

[13]See [19], [47], and [56] for recent results and [41] and [36] for background.

[14]See [57] and the collected works of [66, 67].

2.5 Results

[4] presents a concise argument that the first three or four moments can provide a good approximation of the underlying distribution. Further, it is easy to demonstrate changes in the first three moments of a distribution using simple imagery. Our model will examine the mean, variance and skewness of the health distribution. The following section is presented in two parts: (a) a presentation and discussion of results from the empirical model in Section IV, and, (b) results of several robustness checks to ensure proper specification and consistency.

Table 2.2 presents the main parameter estimates on the raw mean, variance and skewness of the health distribution using ordinary least squares.[15] Autocorrelation and heteroscedasticity consistent standard errors are estimated for all moments and reported in parentheses. All variables are estimated in natural logarithms and each respective coefficient can be interpreted as an elasticity.

Medical care utilization is a significant conditioning variable for all three moments of the health distribution. In reference to the mean specification, we find evidence of "flat of the curve" medicine at the 90 percent level. This suggests that a 10 percent increase in active medical doctors per 100,000 will decrease mortality rates on average by only a tenth of a percent.

However, additional benefits of medical care extend to both the raw variance and skewness of the health distribution. The coefficient on medical care in the raw variance specification, model (2), is negative and significant at the 95 percent level. This implies that increased utilization of medical care will decrease raw variance, thereby potentially reducing the uncertainty of health outcomes. Further, we find not only significant effects from medical care on raw skewness but also reveal a large, negative impact. This implies additional medical care skews the distribution of mortality leftward, thus increasing the probability of having a below average mortality rate. It should be noted this could be due to a small number of

[15] For a full listing of parameter estimates and other statistical tests, please contact the author.

Table 2.2: Regression Results

	Mean (j=1) (1)	Variance (j=2) (2)	Skewness (j=3) (3)
Active doctors	-0.018^{*}	-0.282^{**}	-3.203^{**}
	(0.009)	(0.125)	(1.257)
Percent female	-0.169^{**}	-2.138^{**}	-20.376^{**}
	(0.078)	(1.035)	(10.388)
Percent black	0.014^{***}	0.183^{**}	1.776^{**}
	(0.005)	(0.071)	(0.715)
Percent ≥ 65	0.346^{***}	4.499^{***}	43.970^{***}
	(0.013)	(0.173)	(1.731)
Median income	-0.056^{***}	-0.772^{***}	-7.962^{***}
	(0.015)	(0.201)	(2.018)
Percent bachelors	-0.020^{**}	-0.252^{**}	-2.429^{**}
	(0.009)	(0.121)	(1.218)
Percent obese	0.047^{***}	0.630^{***}	6.304^{***}
	(0.011)	(0.145)	(1.453)
Percent smoke	0.039^{***}	0.517^{***}	5.161^{***}
	(0.011)	(0.143)	(1.435)
Percent ex. drink	-0.011	-0.170	-1.901
	(0.010)	(0.131)	(1.316)
Mean of Dependent Variable	6.68	44.67	299.23
Observations	7,840	7,840	7,840
R^2	0.260	0.256	0.252

*Notes: The dependent variable is the raw moment of log crude death rate: models (1), (2), and (3) represent the mean, variance, and skewness, respectively. All models are estimated under OLS with robust standard errors presented in parentheses. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

outliers as skewness measures are highly influenced by higher-order moments.[16] Regardless, these results clearly indicate positive benefits of medical care outside simple mean or average effects.

Within the lifestyle choice variables, we see substantial significance of both obesity and smoking estimating positive coefficients across all three raw moments. This indicates that higher levels of smoking and obesity lead to not only higher average mortality rates, but also increases in the uncertainty of mortality and the likelihood of above average death rates. In

[16]See [45] and the references within for discussion.

fact, we see a large increase in the net magnitude of these coefficients over those on medical care. In terms of mean effects, the absolute impact of smoking and obesity (0.039 and 0.047, respectively) is more than twice as large the impact on active doctors (-0.018). We see a similar trend in comparing their impact on raw variance and skewness, with smoking and obesity increasing raw variance by almost twice the magnitude of medical care's decrease (0.517, 0.63, and -0.282, respectively). It is interesting to note the negative sign across all three raw moments on excessive drinking; however, it is trivial given their lack statistical significance.

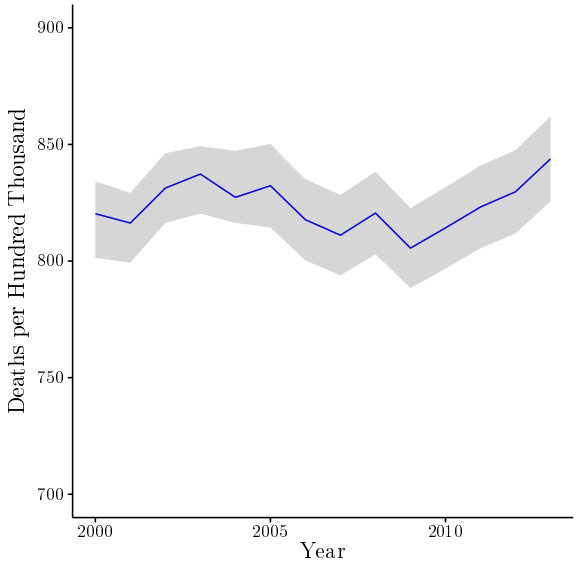
It is of no surprise that the demographic variables are significant in all three equations and follow their expected signs. There are large impacts on all three moments when increasing the proportion of female population and those over 65. Of note, we see incredible effects on raw skewness from these two variables. A 1 percent increase in the population 65 and over increases the rightward (positive) skew of the mortality distribution by the same as 8.6 increase in the percentage who smoke. Similarly, the increased probability of below average mortality from a 1 percent increase in the proportion of females can also be achieved by a 6.6 percent increase in active medical doctors.

A common issue in the literature on health production is the treatment of endogeneity, particularly between dependent health variables and the measurement of medical care. In our context, there is potential for reverse causation to exist between crude mortality rates and active medical doctors. Consider that counties with higher mortality rates (and hence less healthy populations) utilize more medical care. More intuitively, doctors may seek to locate in counties with higher mortality rates since there may exist a financial incentive from high demand. This, if not controlled, can upwardly bias the estimate on medical care utilization.

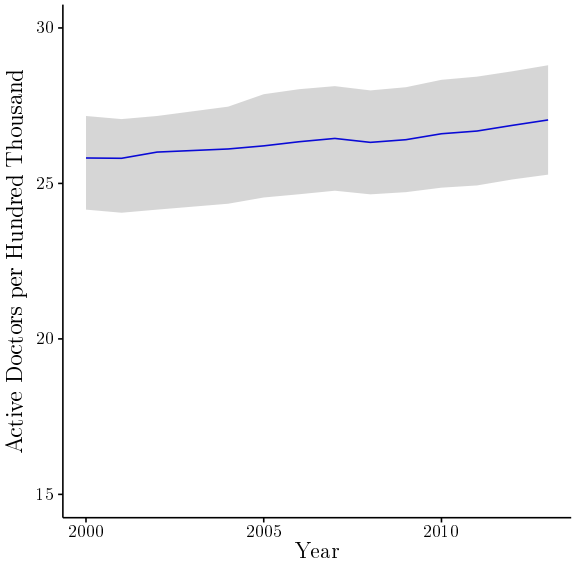
It is worth noting the impact this might have on the causal interpretation of our results. Because of our specification using raw moments, the dependent variable in our variance and skewness equations are positive transformations of the mean dependent variable. This

Figure 2.3: Death Rates and Medical Care

(a) Deaths per 100,000



(b) Average Active Medical Doctors per 100,000



Notes: The graphs above show the the average crude death rate and number of active medical doctors per 100,000 in the population for our sample spanning 2000-2013. Confidence intervals are reported in gray..

relationship preserves not only the sign of each dependent variable but any potential upward bias on the coefficient of medical care across all three moments. So, if endogeneity is present and not controlled, we can state that the raw mean, variance, and skewness effects are correlations but underestimated.

However, we leverage our panel approach to address this issue. We suggest that our county fixed effect is able to capture the "baseline" level of health, and, in this circumstance, be used to tease out the potential endogeneity. To our knowledge, this is the only paper utilizing county-level data and, as such, we will proceed to conduct several robustness checks (including instrumental variables) to test both our bias direction and consistency of results.

We posit three additional specification on our original model from Section IV. The initial two serve as basic robustness checks and the third to address potential endogeneity. First, we estimate a single variate linear model regressing crude death rates on active medical doctors per 100,000. Second, we utilize a pooled OLS model with the full complement of explanatory

variables, removing county fixed effects. Finally, we present a two-stage least squares model. Here, we instrument out active medical doctors with the percent of county population in six age intervals.[17] The distribution of age in each county should not have a direct impact on death rates (given we control for those 65 and older). However, given that county age structure does impact the utilization of medical care, these age distributions should indirectly affect death rate through its effect on active medical doctors. Since the focus of this paper involves the usage of medical care, Table 2.3 presents the estimated coefficient on active medical doctors for each new specification with our original model for reference.

Table 2.3: Robustness Checks

	Coefficient estimate on Active doctors		
	Mean (j=1) (4)	Variance (j=2) (5)	Skewness (j=3) (6)
FE with time effects (main model)	-0.018^{*}	-0.282^{**}	-3.203^{**}
	(0.009)	(0.125)	(1.257)
Single regressor	-0.002	-0.040	-0.572
	(0.006)	(0.079)	(0.789)
Pooled OLS	0.064^{***}	0.823^{***}	7.894^{***}
	(0.003)	(0.038)	(0.381)
IV FE with time effects	-0.019^{*}	-0.382^{*}	-5.406^{**}
	(0.010)	(0.127)	(1.277)

*Notes: The dependent variable is the raw moment of log crude death rate: models (1), (2), and (3) represent the mean, variance, and skewness, respectively. All models are estimated under OLS with robust standard errors presented in parentheses. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

On the whole, each specification maintains a consistently negative sign on all moments with the exception of the pooled OLS model (positive coefficients of 0.064, 0.823, and 7.894 on the mean, variance, and skewness respectively). However, this is not surprising. The pooled model does not feature a county fixed effect and hence ignores the unobservable, time-invariant factors affecting health. This exclusion positively biases the coefficient on

[17] This is similar to the approach taken by [79].

active medical doctors across all three moments and ultimately pushes them into positive values. We do find a slight change in coefficients across all moments in the 2SLS model. While the difference in coefficients is trivial, it may suggest some remaining endogeneity after controlling for time-invariant county heterogeneity.

2.6 Shape Characteristics for a Heath Distribution

The previous section provides parameter estimates that capture how medical care and other inputs affect the moments of a health distribution. However, it is not immediately clear how these factors change the overall shape. Further, evaluating moments under different variable regimes may not fully demonstrate the effects on the distribution of health.[18] In the following subsection, we employ the method of maximum entropy to solve this issue and produce full health distributions conditional on a range of covariates.

2.6.1 Maximum Entropy

This section provides details of the procedure for utilizing the maximum entropy technique. The Principle of Maximum Entropy (PME), as found in [48] and [40], states that the correct specification of an unknown distribution is one which maximizes information entropy (uncertainty) subject to a series of constraints representing evidence or facts known to the experimenter. While there have been many developments in this area, we follow the discussion found in [85] and note the author presents a concise review of the classic methodology.

Given a continuous random variable Y with a density function f, the Shannon information entropy can be expressed by:

$$H(f) = -\int f(y) \ln f(y) dy \tag{2.6}$$

In our case, the density function f is not known; however, the moments of f are known. Given this, PME suggests we should choose a distribution, from all potential variations, that both

[18] This is often called the moments problem originally discussed by [73] and is found in trying to invert the mapping of probabilities measures (a condition density function) to a sequence of moments.

satisfies the moment conditions and maximizes the information entropy in equation (2.6). Our moment conditions are given by,

$$\int f(y)dy = 1 \tag{2.7}$$
$$\int y^k f(y)dy = \mu_k$$

where μ_k is the raw k-th moment and $k = 1, 2, 3$. We can proceed by creating a Lagrangian with our moment conditions as constraints:

$$L = -\int f(y) \ln f(y)dy + \lambda_0 \left(1 - \int f(y)dy\right) + \sum_{k=1}^{3} \lambda_k \left(\mu_k - \int y^i f(y)dy\right) \tag{2.8}$$

where $\lambda_0, ..., \lambda_3$ are the Lagrange multiplier each corresponding to a moment condition from equation (2.8). There are five necessary first-order conditions for an interior solution, and the implied distribution take on the form,

$$f^*(y) = \frac{1}{\zeta(\boldsymbol{\lambda})} \exp\left(-\sum_{k=1}^{3} \lambda_k^* y^k\right) \tag{2.9}$$

where $\lambda_1^*, \lambda_2^*, \lambda_3^*$ are the optimal multipliers and $\zeta = \int \exp\left(-\sum_{k=1}^{3} \lambda_k^* y^k\right) dy$ is a normalizing factor ensuring the density integrates to one.[19] Given equation (2.9) and a set of specific moments, we can estimated the λ values using a sequential-updating method developed in [85].[20]

2.6.2 Density Estimates

In this section, we estimate new maximum entropy distributions under alternative specifications to fully highlight the shape impact of our regressors. Specifically, we demonstrate

[19] The function implied by equation (2.9) encompasses many common densities including the normal, Poisson, beta, chi-squared, Pareto or any member of the exponential class.

[20] There is no analytical solution to equation (2.9) which is common to maximum entropy estimation. The numerical estimation outlined in [85] is advantageous because it (i) solves for density estimates sequentially, updating as it moves from lower to higher moments, and (ii) can include a larger number of moment constraints.

Table 2.4: Moments for Baseline and Shifted Scenarios

Scenario	μ_1	μ_2	μ_3	Scenario	μ_1	μ_2	μ_3
Baseline: Medical Care				Shifted: Medical Care			
Harnett, NC	6.74	45.63	309.62	Harnett, NC	6.74	45.56	308.90
Hendricks, IN	6.68	44.77	300.56	Hendricks, IN	6.68	44.71	299.85
Baseline: Income				Shifted: Income			
Robeson, NC	6.82	46.59	319.07	Robeson, NC	6.81	46.53	318.35
Loudoun, VA	6.43	41.51	268.28	Loudoun, VA	6.43	41.44*	267.56
Baseline: Smoking				Shifted: Smoking			
Davis, UT	6.54	42.91	282.49	Davis, UT	6.53	42.85	281.78
Muskogee, OK	6.89	47.44	327.09	Muskogee, OK	6.88	47.38	326.38
Baseline: Obesity				Shifted: Obesity			
Denver, CO	6.65	44.31	295.44	Denver, CO	6.65	44.25*	294.73
Portsmouth, VA	6.83	46.68	319.30	Portsmouth, VA	6.83	46.62*	318.58

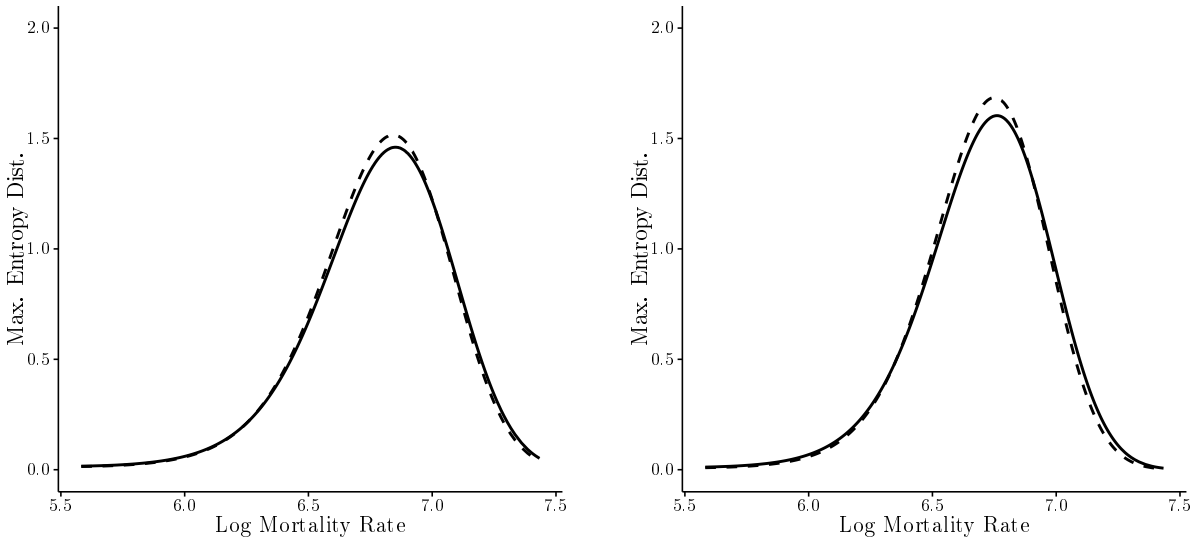
*This table reports the estimated moments for the Maximum Entropy estimator of the health distribution for both baseline and shifted regions. For the shifted regimes, we include asterisks to denote statistically significant differences relative to each county?s baseline counterpart. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

the flexibility of this approach by producing different county-level health distributions under two medical care regimes. Our baseline specification is simply to evaluate county estimates at their sample means. This is intended to produce a current health distribution. Our second, "shifted" regime involves a 10 percent increase in the number of medical doctors per hundred thousand in the population. This should provide additional clarity to the marginal impacts of medical care on the moments of the health distribution.

One might suggest creating a representative county by averaging across our entire sample and building out a distribution from there. However, this does not capture the county heterogeneity we strive so hard to account for in the previous sections. Nor is it practical to present maximum entropy distributions on every county in our sample. We choose to examine counties who occupy the upper and lower ends of our other explanatory variables. We select counties whose average values are at the 10th and 90th percentile for each of the following variables: medical care (10th percentile: Harnett County, NC; 90th percentile: Hendricks

Figure 2.4: Maximum Entropy Distributions: Medical Care

(a) Harnett, NC (b) Hendricks, IN



Notes: All the above distributions are constructed using a maximum entropy technique. The baseline distribution features a solid line while the medical care shifted distribution is dashed.

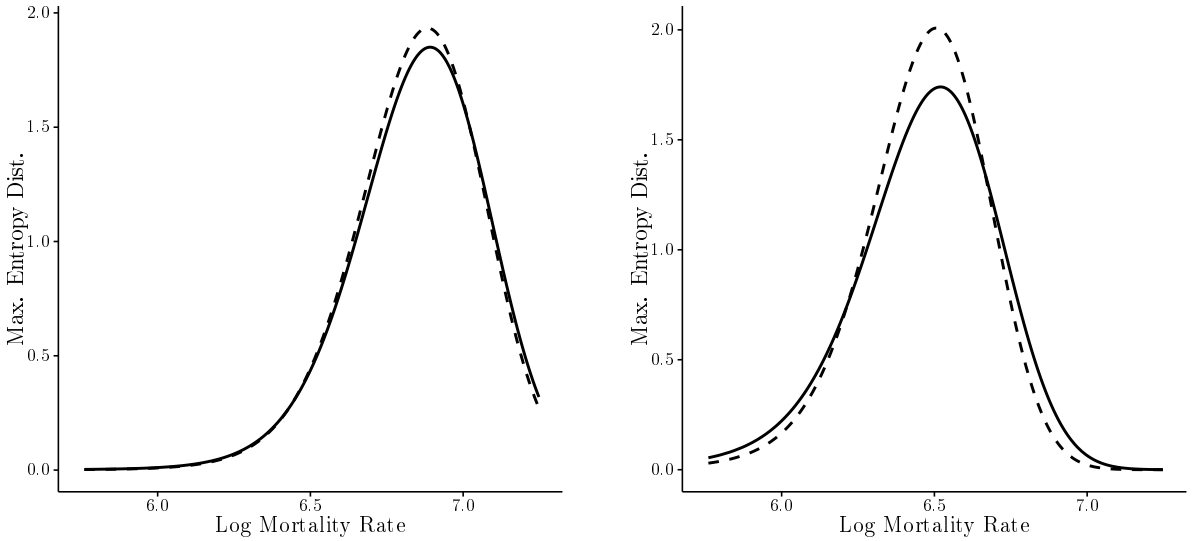
County, IN), income (10th percentile: Robeson County, NC; 90th percentile: Loudon, VA), smoking (10th percentile: Davis, UT; 90th percentile: Muskogee, OK), and obesity (10th percentile: Denver County, CO; 90th percentile: Portsmouth City, VA).

The baseline distributions are constructed using the county-specific average data and the coefficients from Table 2.2 to generate predicted moments. These moments are then placed as constraints in our maximum entropy problem. As discussed before, we simulate an uptick in medical care by increasing the overall number of doctors in each county by 10 percent, recalculating average data and following the baseline procedure from there. To ensure consistency, all other variables are held constant at the sample averages.

Table 2.4 presents the estimated moments under the eight different scenarios previously outlined. We denote with asterisks those moments under the shifted regime whose values are statistically different that their baseline counterparts. We are unable to report any significant differences in mean regime effects for any county we examine. This is not surprising given the low marginal product of medical care estimated in the previous section. We do find

Figure 2.5: Maximum Entropy Distributions: Income

(a) Robeson, NC (b) Loudoun, VA



Notes: All the above distributions are constructed using a maximum entropy technique. The baseline distribution features a solid line while the medical care shifted distribution is dashed.

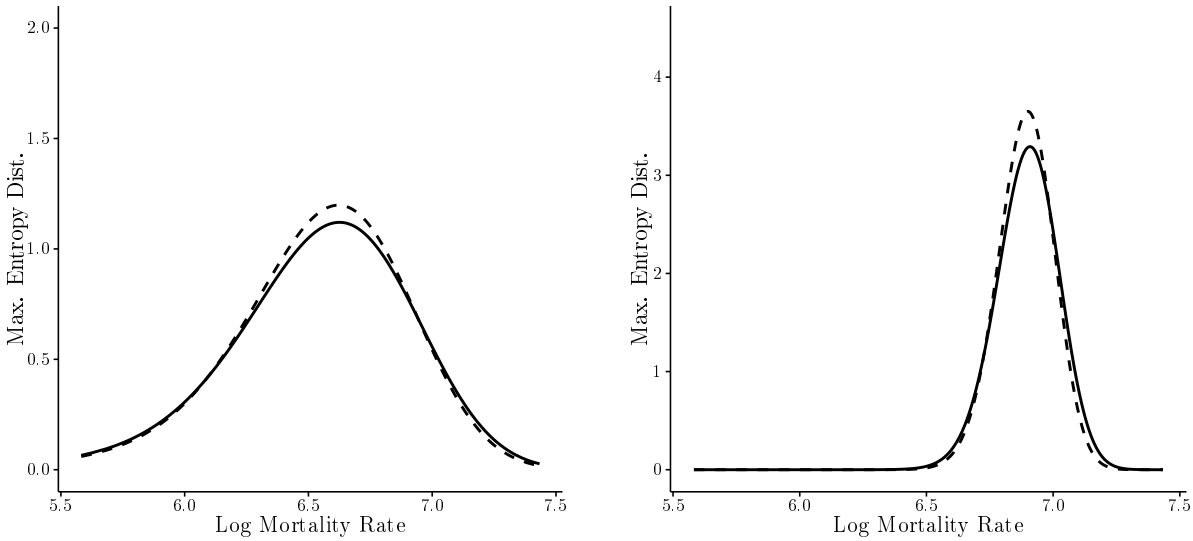
significant differences in the second raw moment in high income counties (Loudoun, VA) and counties with extreme differences in obesity rates (Denver, CO and Porstmouth, VA respectively). In all three case, we see average raw variance decreases in the shifted regime.

Figures 2.4, 2.5, 2.6, and 2.7 present the maximum density estimations under the two regimes for medical care, income, smoking and obesity respectively. Baselines distributions are plotted using a solid line while the shifted distributions are dotted. There are several notable patterns to discuss. In all four figures, we see that the shifted distributions (having 10 percent more doctors per hundred thousand) feature probability mass above their baseline counterparts. This suggests medical care induces at the very least a decrease in variance and possibly a mean-preserving contraction in probability. This represents a significant source of welfare as, in all the scenarios presented, we see a decrease in mortality risk.

Focusing specifically on income in Figure 2.5, we find evidence that counties with higher levels of income exhibit a larger decrease in overall health variability than lower income counties. The literature currently supports evidence that higher income leads to better

Figure 2.6: Maximum Entropy Distributions: Smoking

(a) Davis, UT (b) Muskogee, OK



Notes: All the above distributions are constructed using a maximum entropy technique. The baseline distribution features a solid line while the medical care shifted distribution is dashed.

health or, in this case, lowered mortality.[21] However, Figure 2.5 provides new evidence that health (mortality) is more certain with higher levels of income. The most apparent impact of medical care on the distributional spread can be found in examining differing levels of obesity in Figure 2.7. For both high and low prevalence of obesity, we see significant contraction of probability around the mean.

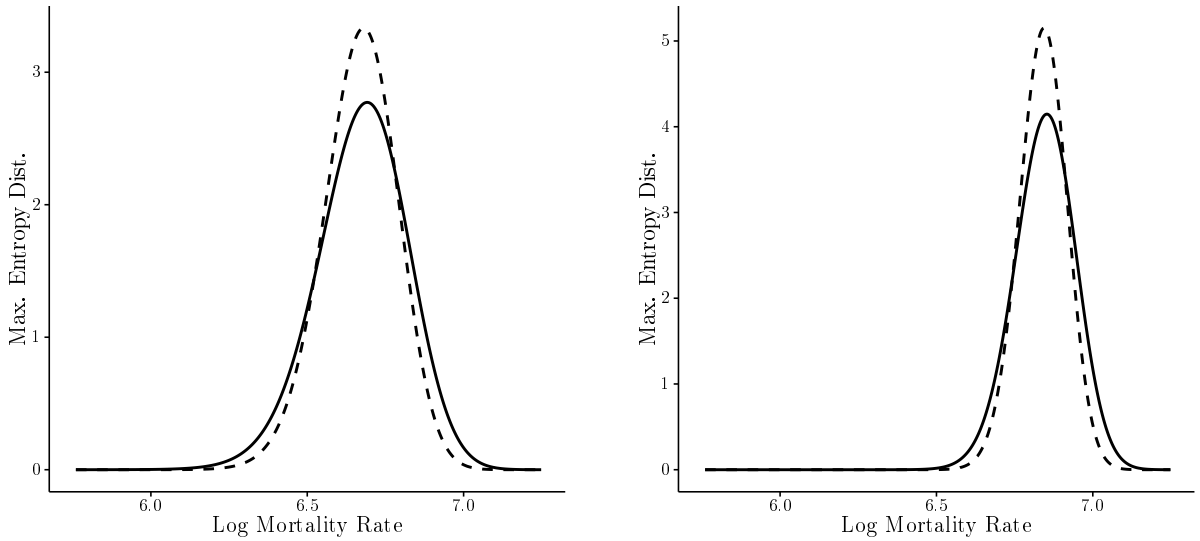
2.7 Conclusion

This study suggests a more realistic framework for estimating health production by introducing a random or stochastic component. We present a flexible method to link a set of explanatory variables to the moments of a health distribution, demonstrating how these covariates affect its overall shape. Using a set of county-level US data, we find evidence of "flat of the curve" medicine, showing that a 10 percent increase in medical care utilization decreases average mortality rates by only a tenth of a percent. However, given the stochastic

[21] See the mode location of each distribution in Figure 2.5.

Figure 2.7: Maximum Entropy Distributions: Obesity

(a) Denver, CO (b) Portsmouth, VA



Notes: All the above distributions are constructed using a maximum entropy technique. The baseline distribution features a solid line while the medical care shifted distribution is dashed.

specification, we show increased medical care reduces the overall variance of mortality rates and leads to a more negative skew of its underlying distribution. These secondary and tertiary benefits are otherwise ignored by the existing empirical literature. We further examine these impacts using our estimated moments to construct maximum entropy distributions, which allow us to show how medical care changes the overall shape of the health distribution. We then provide visual representation of the impacts of medical care, showing decreases in the overall spread of the health distribution under various scenarios.

We feel this paper serves as an initial step to examining the higher-order effects of choice variables on health. It seems natural for future research to assess the economic impact of these distributional changes. Quantifying these benefits might provide explanations for a myriad of medical care market phenomena. Also, the additional utilization of medical care may lead to improvements in the quality of life and its associated distribution. Future extensions of this work should include consideration and measurements of not only duration of life, but quality as well.

CHAPTER 3

IRRIGATION AS SELF-PROTECTION: AN ANALYSIS ON CROP YIELDS

3.1 Introduction

Farmers face a number of risks in the planning, production and distribution of their crops. For better or worse, they face an equally large number of ways to handle these risk. Two of the most widely used risk-management tools are irrigation and insurance. While there are volumes of research on the practices individually, to our knowledge, no one has considered estimating the relationship between the two.

Ideally, a representative demand model for either irrigation or insurance could be constructed and the corresponding relationship pulled out. However, price information for either practice proves limited. Wide-scale data on irrigation technology cost is simply unavailable and the variable cost of irrigation, water, is inconsistent at best. There exists a bevy of data on crop insurance; however, independence is problematic given the federal government's heavy subsidization of premiums.

In this paper, we circumvent these limitations by viewing the insurance-irrigation relationship within the theoretical framework established by [30]. In their seminal work examining the risk-management options of a consumer, they introduce the concepts of self-protection and self-insurance. Broadly stated, self-protection relates the expenditure of resources to the reduction in probability of a loss while self-insurance incurs cost to reduce the size of a loss in the event of its occurrence. Given these somewhat general definitions, there is a wide degree of ambiguity in how these concepts relate to irrigation. One could certainly consider weather variation a source of risk and to that extent, consider irrigation a form of self-insurance, reducing the size of overall crop loss from poor rainfall by supplementing soil

moisture. However, when we consider the additional layers of risk including crop disease, pests, price distortions, and more, it may be more general to think of irrigation as self-protection, changing the probability of a multi-peril loss situation. It is this generality that lead us to believe irrigation is self-protection. Fortunately, we can confirm this relationship by examining the correlation between irrigation and traditional market insurance.

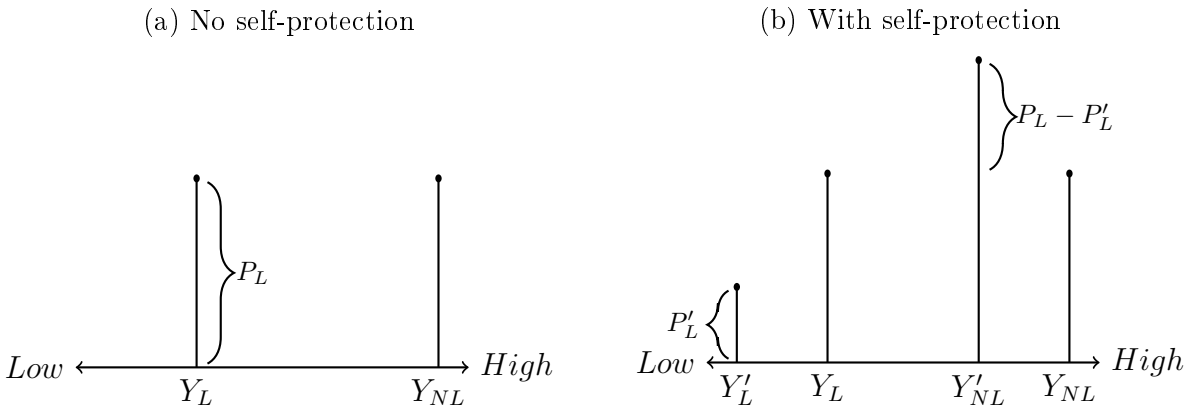
As noted in [30], the trade-off between these risk-management options depends on the relationship between premiums and the level of self-protection. In our context, if an insurer is able to account for a farmers level of irrigation and include this in premium calculations, then insurance encourages the adoption of irrigation (self-protection). If insurers are unable to verify irrigation practices, farmers have no incentive to self-protect and the relationship is inverse. This is generally considered a case of moral hazard, where farmers will fail to engage in protective strategies, like irrigation, when insured.[1]

We examine this relationship by modeling the crop yields of two commodities, corn and soybeans, using county-level data on weather, insurance coverage, and irrigation practices. More specifically, we use an interacted effect of irrigation and insurance to tease out their specific relationship. The key identifying assumption is that farmers seek to maximize expected profit through maximizing expected yields. To that extent, farmers who both insure and irrigate their field should see higher yields if the practices are complementary or lower yields if they are substitutes. Using this logic, we find evidence that a complementary relationship exists for both corn and soybeans, suggesting irrigation is a form of self-protection. We then employ a generalized technique to show the impact of irrigation on higher moments of the yield distribution.

Our paper will proceed as follows. In Section II we further develop the self-protection model and give a brief discussion of crop insurance. Section III explains our mean model for crop yields including a detailed discussion of the interaction terms. Section IV describes the data we use in our analysis and Section V presents our results. Section 6 implements a

[1] There are worthwhile discussion on the risk-attitude implications of self-protection models in [11] and [50]

Figure 3.1: A Simple Explanation of Self-protection



Notes: Initial, in the left panel, a farmer faces a high yield outcome Y_0 with probability $1 - P_L$ and a low yield outcome with probability P_L. After self-protection, the probability of loss is lower, $P`_L < P_L$, both both the high and low yield outcomes have moved left, Y'_0 and Y'_L respectively.

technique to regress our data on higher moments of the yield distribution to further address the irrigation-insurance relationship. Finally, we conclude in Section VI.

3.2 Crop Insurance and Self-protection

Consider a simple example where a farmer faces an exogenous risk with a binary outcome; either poor yields with a probability of P_L or good yields with probability $1 - P_L$. The left-hand grpahic in Figure 3.1 provides an illustration with Y_{NL} and Y_L representing good and poor yields and the height of each mass point reflecting probability. The right panel shows a farmer engaging in self-protection, possibly irrigation. Note first, there is an immediate reduction in both levels of yield between the good and bad states due to the self-protection expenditure. Second, since the size of the loss is unaltered, in the event of a loss, the farmer would be in an even worse position than if no self-protection had taken place. Third, since the likelihood of loss changes, probability mass shifts towards the higher state. While we cannot specifically say what happens to the spread of the distribution, we do find an unequal balance of probability around the mean. In fact, if irrigation is self-protection, we should see centered skewness decline (i.e. the distribution is skewed left). We provide evidence of this effect in Section VI

As mentioned in the introduction, the ultimate relationship between irrigation and insurance rests on the monitoring ability of insurer. Crop insurance is not only a widely used risk management tool but also an increasingly popular mechanism to deliver federal agricultural policy. The federal government has been involved in the Federal Crop Insurance Program (FCIP) and the provision of Multi-Peril Crop Insurance (MPCI) since the late 1930's.[2] Originally intended to fill the lack of private contracts due to strong spatial loss correlations, the FCIP has evolved through the years under various legislative and policy effects. Notably, the Agricultural Adjustment Act of 1980 greatly expanded the number of crops covered under the FCIP and first swayed farmers to adopt coverage by subsidizing some of their premium expense. Participation in the FCIP program was made mandatory under the Federal Crop Insurance Reform Act of 1994 but was repealed two years later in the 1996 Farm Bill.[3] This however, marks a point from which FCIP participation and coverage have only increased. According to the Risk Management Agency (RMA), a division of the Department of Agriculture that oversee all FCIP initiatives, since 1994 the number of acres insured has increased by over 300 percent and included nearly 86 percent of all eligible acres (up from 33 percent in 1994).[4]

Today, the FCIP serves two main functions: the regulation of policies and premium expenses and providing transfer payments to farmers in the form of premium subsidies. Under current guidelines, a farmer decides both the type of insurance policy and what level of coverage, However, the coverage options and policy premiums are set by the RMA and administered by private insurance agencies. Subsidies cover both premium cost from production risk and A&O expenses from the insurance companies. As of 2015, government subsidies make up nearly 61 percent of premiums paid. This could provide financial incentive for farmers to adopt higher levels of coverage, and, if irrigation is a form of self-insurance,

[2]Also referred to as yield insurance or APH (Actual Production History), MPCI indemnifies contract holders against losses falling below a specified yield.

[3]For a detailed listing of legislative and policy changes, visit the RMA's website, `www.rma.usda.gov`

[4]Total acres can be found at the National Agricultural Statistical Service (NASS) and insured acres using the RMA's Summary of Business.

lead to potentially higher levels of water use.

3.3 Mean Model

This research presents a panel model regressing crop yields y_{it} on a set of weather, insurance, and irrigation variables following:

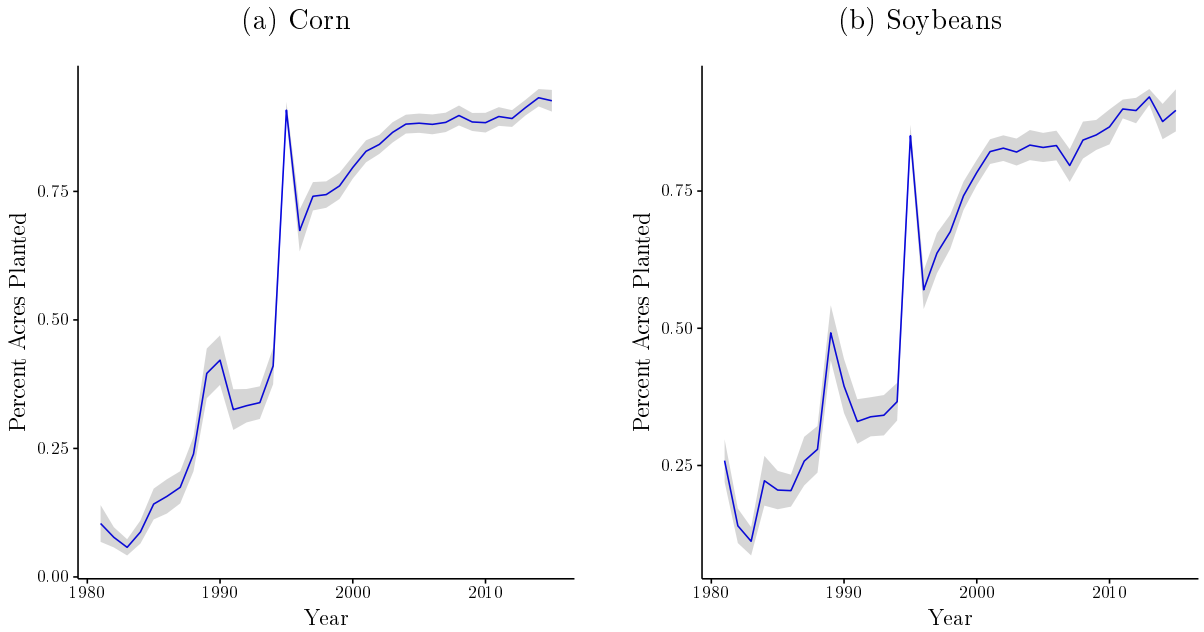
$$\begin{aligned} y_{it} =& \alpha_i + \rho_t + h_i(t) + \beta_1 mod_{it} + \beta_2 high_{it} + \beta_3 prec_{it} + \beta_4 prec_{it}^2 + \beta_5 irr_{it} + \beta_5 ins_{it} \\ &+ \gamma_1(ins_{it} * mod_{it}) + \gamma_2(ins_{it} * high_{it}) + \gamma_3(ins_{it} * prec_{it}) + \gamma_5(ins_{it} * prec_{it}^2) \\ &+ \delta_1(irr_{it} * ins_{it}) + \delta_2(prec_{it} * ins_{it}) + \delta_3(irr_{it} * prec^2)_{it} + \epsilon_{it} \end{aligned} \tag{3.1}$$

We include county-fixed effects α_i to control for consistent land productivity not captured by the remaining variables. We also include time-fixed effect ρ_t to account for country-wide changes in the administration of crop insurance. Figure 3.2 highlights some of these important years as insurance coverage levels shift in and around policy changes, particularly 1994-1995. The time effect also controls for an change in available farming technology. Figure 3.3 shows a upward trend in yield pattern for both corn and soybeans. Given this, we incorporate a county-specific quadratic time trend, though we present robustness checks with both state-specific time trend and sample wide trend in the Appendix. The remaining variables are discussed in brief below with details on specific measures and calculations in the next section.

Temperature variables *mod* and *high* measure the degree of moderate and extreme heat respectively. Rainfall is accounted for in *prec* and we include $prec^2$ to capture any quadratic relationship. The availability and usage of irrigation technology is captured in *irr* and insurance coverage by *ins*.

The remaining variables of equation (3.2) pertain to interaction terms. The first block includes an interaction of insurance coverage with the full complement of weather variables. This is largely based on the results of [3] who find that farmers attend differently to extreme

Figure 3.2: Insurance



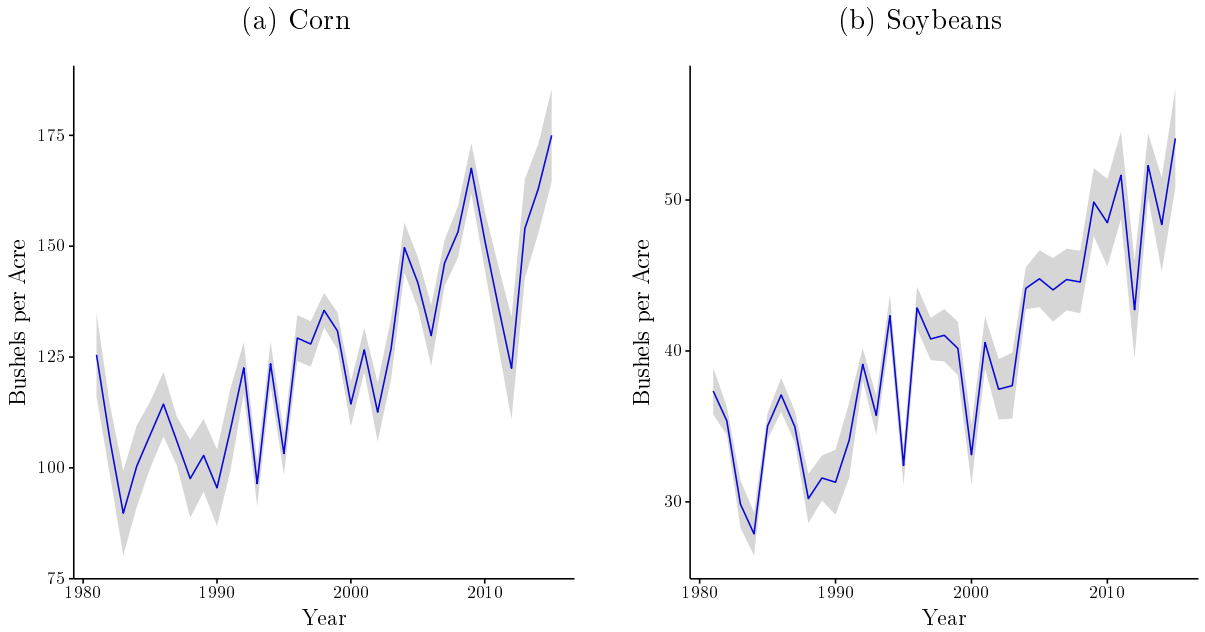
Notes: The graphs above show average fraction of planted acres insured for both corn (left) and soybeans (right) from our sample ranging from 1981-2015. Standard 95% confidence bands are highlight around each observation.

weather fluctuations when insuring those crops. The second block includes an interaction of irrigation on both insurance coverage and precipitation. In fact, δ_1 is our parameter of interest. This provides an estimate of how insurance coverage impacts the benefits of irrigation. A positive relationship suggest irrigation is a form of self-protection while a negative value implies either self-insurance or moral hazard. Interactions between irrigation and precipitation are included to account for the structural difference between non-irrigated (dryland) and irrigated acreage.[5]

The interaction terms also serve an important role in addressing concerns of endogeneity. First, one might suspect that farmers could respond to yield shocks with subsequent irrigation practices. However, considering the significant financial cost associated with irrigation technology, this is unlikely. Further, an outlier event resulting in wide-scale decreases (or increases) of irrigation would be captured in both the precipitation and temperature vari-

[5] [59], [68], and [76] all present evidence that pooling dryland and irrigated acreage bias estimates on precipitation due to differences in the yield relationship.

Figure 3.3: Yield



Notes: The graphs above show average yield for both corn (left) and soybeans (right) from our sample ranging from 1981-2015. Standard 95% confidence bands are highlight around each observation.

ables included in the model. Second, there is potential for yield variation to impact the level of insurance coverage in subsequent years. This is trivial however as we are not interested in that specific coefficient. Since we interact a potentially endogenous variable *ins* with an exogenous set of weather and irrigation variables, the respective interaction parameters can be interpreted as exogenous as long as we control for the single effect of the endogenous variable. We also assume that both the outcome variable and the endogenous variable are jointly independent of the exogenous variables. [6]

3.4 Data

Descriptive statistics for the data are reported in Table 3.1. The set is an unbalanced panel of publicly-available, county-level data for corn and soybeans from 1981-2015.[7] We have a total of 3,053 observations on corn comprised of 1,323 from Kansas counties, 1,202 from

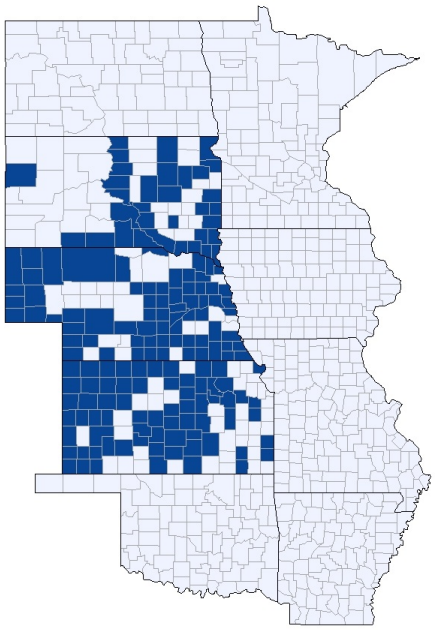
[6] See [2], section 2.3.4, [12], and [61] for reference and discussion.

[7] County-level data is common to the literature due to its available long time series and disaggregated level. It should be noted that county level variability will be less than farm-level.

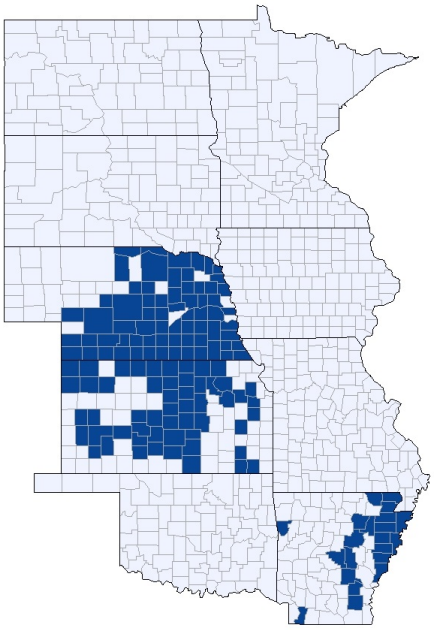
Nebraska, and 528 from South Dakota. For soybeans, we have a total of 2820 observations comprised of 290 from Arkansas counties, 859 from Kansas, and 1.671 from Nebraska. Data locations can be seen in Figure 3.4.

Figure 3.4: Data from 1981-2015

(a) Corn



(b) Soybeans



Notes: The dataset consists of 3.053 observations for corn and 2,820 observations for soybeans from the period 1981-2015.

Data on county-level commodity production, acreage planted, and irrigation are collected by the National Agricultural Statistical Service (NASS). Yield measures for both corn and soybeans are the ratio of production to acres planted and reported in bushels per acre. Since 1965, the NASS distinguishes between irrigated and dryland acreage by crop. However, the distinction is not required in all yearly surveys and to that extent limits the number of counties we can observe. To add robustness, we include only counties (i) with at least 10 consecutive years of observations and (ii) whose total state observations make up more than 10 percent of the overall crop-specific data. Irrigation measures examine the ratio of irrigated acres planted to total acres planted for each commodity. Irrigated acres, as defined by the NASS, involves any acreage which receives at least one application of water during

the growing season. We discuss the implication of this in the next section.

County-level insurance data is collected by the Risk Management Agency (RMA). Data including number of policies and acreage insured is available from 1981 until present and is the primary reason for the years spanning our dataset.[8] For our study, we construct the fraction insured variable by taking the ratio of insured acres over the total planted acreage for each commodity.[9]

It is important to note that the RMA and NASS calculate county aggregates using different methodologies.[10] The NASS data features some sampling noise as it is estimated from the June Agricultural Survey. As a result, the fraction of planted area insured can exceed one if the sampling noise in the NASS understates the planted acreage. Among other things, this sampling noise can blur identifying the effects of county-specific time trends which depend on annual deviations. To combat this, we follow [3] and use the maximum of the reported planting area in each county as the denominator, which by definition is constant for each county.[11] It is also noted in previous work that overestimating planted acreage can occur in circumstances of double-cropping, planting and harvesting more than once in a season. However, this is unlikely given both the specific crops we examine and the growing season here in the US.

We use weather data from the PRISM weather system and methodology first popularized by [69]. PRISM is a high resolution, 2.5×2.5 mile grid of weather stations, covering the contiguous United States, collecting daily readings on maximum and minimum temperatures, average temperature, and precipitation.[12] [69] employ a sinusoidal curve to fit daily distributions of temperatures through their respective minimum and maximum readings.

[8] Data on subsidies and premium expenditures are available starting in 1989. To that extent, we provide estimation results for equation 3.2 using only data from 1989-2015 in Table 3.8 of the Appendix. We see no significant change in any of our findings.

[9] Observations where the fraction insured is greater than one are topcoded to one.

[10] See [3] for a detailed discussion of these differences

[11] Figure 3.7 in the Appendix shows the number of times the annual insured area exceeds the maximum of the planted area for either corn or soybeans.

[12] The set of weather stations in each grid is held constant over time, ensuring that variation in data is due to weather and not reporting stations. Detailed daily data is available from 1950 to the present. This paper accessed the raw PRISM daily data via AgAnalytic at www.ag-analytics.org

Table 3.1: Variable List, Definitions, and Descriptive Statistics

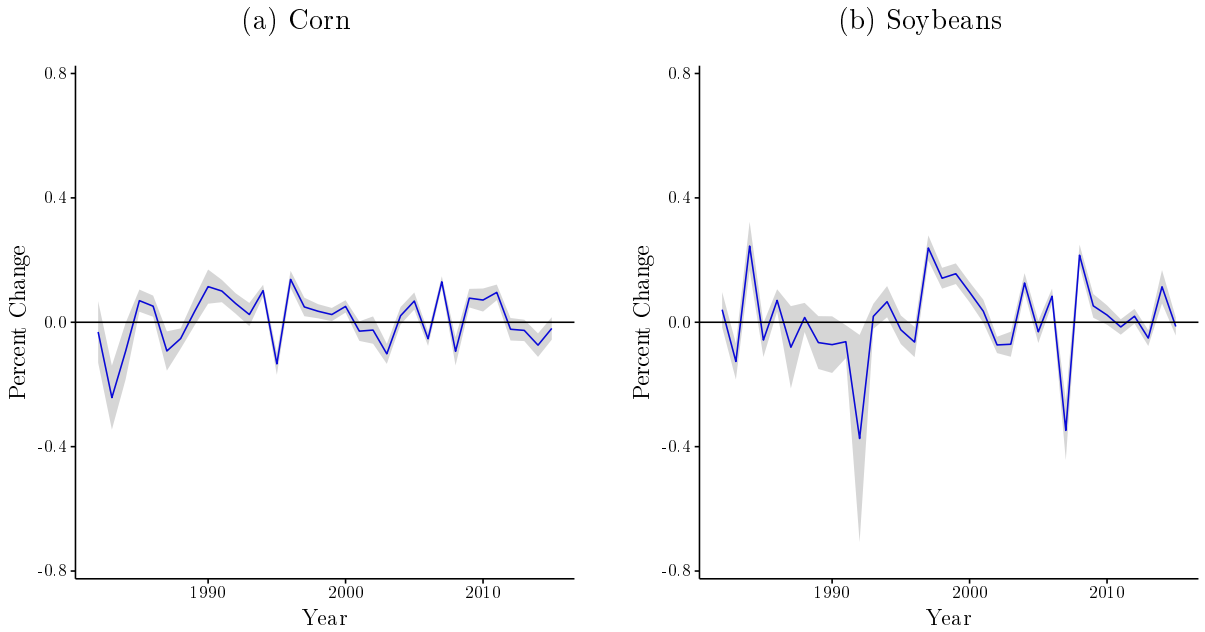
Variable name, Variable (Description)	Mean	St. Dev.	Min	Max
Corn (n=3053, counties = 170)				
Yield, *y (bushels per acre planted)*	124.28	36.34	25.90	224.00
Fraction Irrigated, *irr (fraction of planted acres)*	0.52	0.35	0.003	1.00
Fraction Insured, *ins (fraction of planted acres)*	0.64	0.32	0.002	1.00
Precipitation, *prec (total in meters)*	0.56	0.17	0.14	1.28
Moderate heat, *mod (degree days* $10 - 29°C$*)*	1,877.32	283.44	1,091.01	2,696.75
Extreme heat, *high (degree days above* $29°C$*)*	36.23	28.52	0.10	190.19
Soybeans (n=2820, counties = 143)				
Yield, *y (bushels per acre planted)*	39.20	10.04	12.00	68.50
Fraction Irrigated, *irr (fraction of planted acres)*	0.48	0.32	0.001	1.00
Fraction Insured, *ins (fraction of planted acres)*	0.60	0.30	0.003	1.00
Precipitation, *prec (total in meters)*	0.63	0.18	0.25	1.65
Moderate heat, *mod (degree days* $10 - 30°C$*)*	2,023.37	331.34	1,359.71	3,098.06
Extreme heat, *high (degree days above* $30°C$*)*	35.48	25.05	0.47	151.55

Notes: Both temperature and precipitation variables correspond to the April through October growing season.

The authors then construct the time spent at 1°C intervals between −5°C and 50°C. Each interval's time outcome is the area-weighted average of all grids in a county.

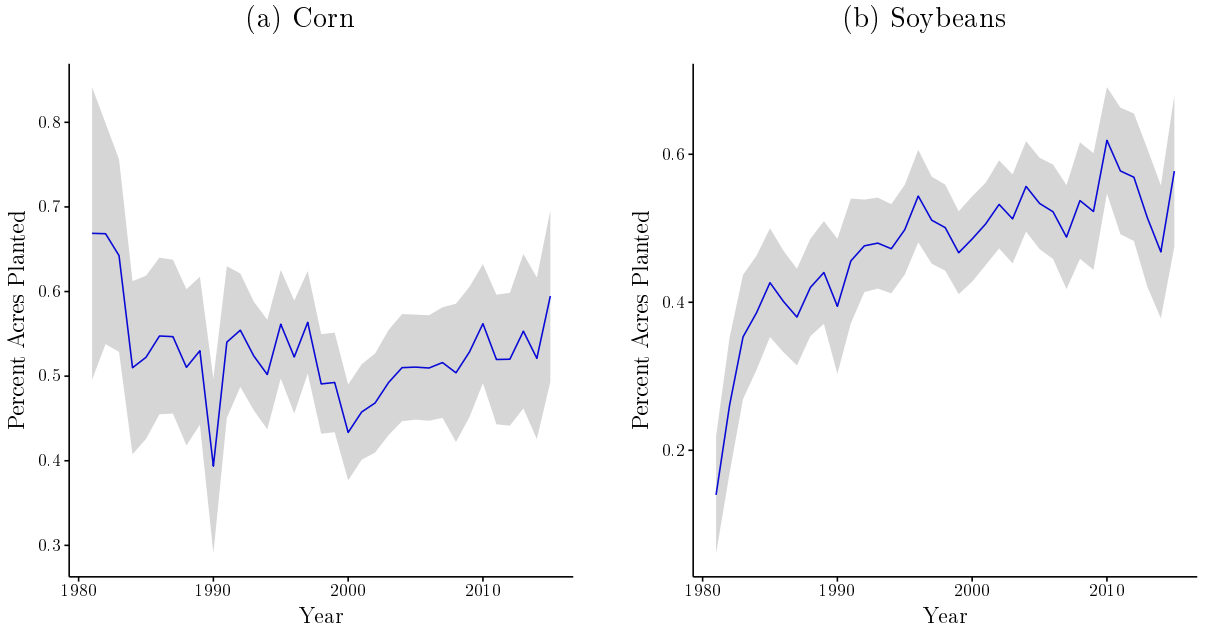
Using this technique, we examine two measures of temperature. The moderate heat measure is constructed by subtracting the number of degree days above 10°C by the number of degree days above 29°C for corn and 30°C for soybeans. This captures the range of degree days between those temperature. The extreme heat measure is simply the number of degree days above 29°C for corn and 30°C for soybeans. Finally, we sum over the daily, area-weighted county observation on rainfall to build out a total precipitation measure, reported in meters. All weather variables are constructed over the in-season growing period, April through September.

Figure 3.5: Percent Change in Planted Acres



Notes: The graphs above show the average percent change in planted acreage from year to year for both corn (left) and soybeans (right) in our sample ranging from 1981-2015. Standard 95% confidence bands are highlight around each observation.

Figure 3.6: Irrigation



Notes: The graphs above show average fraction of planted acres irrigated for both corn (left) and soybeans (right) from our sample ranging from 1981-2015. Standard 95% confidence bands are highlight around each observation.

3.5 Results

Table 3.2 presents selected parameter estimates using OLS with standard errors clustered by year to control for cross-county, cross-state spatial correlation. The model is presented both with the preferred interaction terms and without to see if our results replicate the existing literature. Note that the preferred model specifications are in columns marked *b*. Many of the coefficients on weather variables follow their expected signs for both corn and soybeans. We see significant evidence of the positive and diminishing marginal benefits of precipitation and the negative impacts of extreme heat for both commodities.[13] As to whether insurance impacts a farmer's response to weather, our results are mixed. Just as in [3], we do find that insured corn acreage suffers more yield loss under extreme temperatures than uninsured, interpreting the summation of parameters on both extreme heat and it's interaction as the impact of high heat on insured land. In addition, we find new evidence of insurance reducing the yield benefits of precipitation on corn. This follows similar logic to temperature in that farmers who have insurance coverage may not adapt their practices to fully realize the benefits of precipitation. We are unable to replicate weather-insurance effects for soybeans.[14]

As it pertains to irrigation, we find significance on our main variable and all included interaction terms for both corn and soybeans. As expected, we see precipitation more than wholly offsets the positive marginal effect of irrigation, as the parameters on the irrigation-precipitation interaction (-176.31 for corn and -73.57 for soybeans) are larger in absolute value than the main irrigation effects (139.75 for corn, 43.56 for soybeans). It also appears this reversal is increasing in precipitation, with positive coefficients on the interacted quadratic terms. These results are intuitive and expected given that both irrigation and precipitation

[13] We do record a significant and negative coefficient on precipitation in the un-interacted model for corn (1a). We disregard this finding given that the model does not account for the structural difference between irrigated and dryland as mention in Section III

[14] Previous work from [69] and [68] suggest that excluding cold temperatures might bias the impact of extreme heat, although cold measures have not proven significant. Table 3.6 in the Appendix presents a model including a *low* measure capturing degree days between $0 - 10°$C. There is no effect on our main parameter of interest but we do see some variation in both sign and significance on moderate heat.

Table 3.2: Regression Results

	Corn		Soybeans	
	(1a)	(1b)	(2a)	(2b)
Fraction irrigated	83.071***	139.745***	19.327***	43.561***
	(2.699)	(8.242)	(0.876)	(2.918)
x fraction insured		13.571***		12.605***
		(3.275)		(1.099)
x precipitation		−176.305***		−73.574***
		(25.975)		(8.126)
x precipitation^2		85.716***		32.106***
		(20.649)		(5.655)
Moderate heat	−0.009	0.005	0.007***	0.009***
	(0.006)	(0.008)	(0.002)	(0.002)
x fraction insured		−0.008		−0.002
		(0.007)		(0.002)
Extreme heat	−0.260***	−0.178***	−0.132***	−0.150***
	(0.020)	(0.040)	(0.010)	(0.018)
x fraction insured		−0.133**		0.003
		(0.054)		(0.024)
Precipitation	−21.672**	133.561***	21.912***	71.599***
	(10.930)	(22.251)	(3.358)	(7.459)
x fraction insured		−66.273**		−10.207
		(27.868)		(10.108)
Precipitation^2	19.845**	−70.024***	−11.529***	−39.705***
	(7.711)	(15.681)	(2.075)	(4.899)
x fraction insured		45.599**		9.473
		(21.392)		(7.033)
N	3,053	3,053	2,820	2,820
R^2	0.399	0.436	0.266	0.372

*Notes: The table above shows results for regressing crop-specific yield on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.*

are substitutes as means of delivering water to crops.

More notably, we see a positive and significant impact of insurance on the marginal benefits of irrigation. A one percent increase in insured acreage enhances the yield from a similar increase in irrigation by 0.13 bushels per acre for corn and 0.12 bushels per acre for soybeans.[15] Given our control of confounding variation tied to county and time effects, we

[15]Technically, the total effect of irrigation on insured acreage can be determined by summing coefficients

interpret insurance as having a complementary relationship with irrigation. As mentioned in Section II, this suggests that irrigation is a means of self-protection, reducing the probability loss within a yield distribution conditional on stochastic components. More plainly, a farmer insuring more irrigated land ultimately changes their behavior to increase overall yield. It should be noted that this result could also be explained by qualitative differences in insured lands (i.e. marginally insured acreage is more apt to benefit from irrigation). However, this is unlikely for several reasons. First, we include county-fixed effects, time-fixed effects, and trend variables to capture land heterogeneity during a period in which, as Figure 3.2 shows, insurance coverage is rising substantially.[16] Second, given that irrigation and precipitation are effectively substitutes, then one would expect to see a similar, positive effect of precipitation on insured lands. However, as our results show, this is not the case.

3.6 Variance and Skewness Models

The results from the previous section demonstrate that insured and irrigated land results in higher average yields than irrigated, uninsured land, suggesting irrigation acts as a form of self-protection. We now move to understand how this relationship extends to the shape of the yield distrubution. Recall from Section II, farmers engaging in self-protection will decrease both the minimum and maximum states under uncertainty but also negatively skew the overall distribution. Using a methodology outlined in the next subsection, we estimate the impact of irrigation and insurance on the moments of the yield distribution and how their relationship affects the its shape.

3.6.1 Conditional Moment Estimation

This technique is primarily based on the work of [4, 5] and is a growingly popular method for modeling crop yields.[17] Consider the following generalized stochastic production function

on the main and interacted variables assuming zero precipitation. While this may be impractical, one could easily generate overall impacts by evaluating the fitted model at sample means.

[16] This implies that marginal decisions on what land to insure change dramatically within our sample; an unlikely result if insured land was qualitatively different.

[17] See [22] and [76] For applications outside of agriculture, see [84]

for crop yield,

$$y = g(x, v) \tag{3.2}$$

where x is a vector of exogenous, choice inputs and v a vector of random variables reflecting the uncontrollable factors of output. Using the original specification in [4], we can estimate the probability distribution of the stochastic production function as follows,

$$g(x, v) = f_1(x, \beta_1) + \tau \tag{3.3}$$

where $f_1(x, \beta_1) \equiv E[g(x, v)]$, the mean of $g(x, v)$ and $\tau \equiv g(x, v) - f_1(x, \beta_1)$ is a random variable with $E(\tau) = 0$. This is of significance in that it links the conditional moment, in this case the mean, to our explanatory vector x. That said, higher moments of $g(x, v)$ are given by,

$$E\left([g(x, v) - f_1(x, \beta_1)]^k | x\right) = f_k(x, \beta_k) \tag{3.4}$$

where k indicates the particular central moment of interest. This analysis is often called the Linear Moment Model (LMM) and allows for a common set of covariates to explain any conditional moment. However, the LMM approach relies critically on the residuals of the mean equation as the dependent variable in models of higher-order moments. This implies that any bias due to modeling error will bias all sequential moment equations.[18] A more robust solution is to examine the raw moments of the yield distribution using the following system of equations,

$$[g(x, v)]^j = f_j(x, \beta_j) + \epsilon_j \tag{3.5}$$

[18] [76] discusses the shortcomings of LMM approach and several other moment conditioning techniques. It should also be noted that the LMM exhibits severe heteroskedasticity as the variance of lower moments models are dependent on higher order models.

where j indicates the particular raw moment of interest. While the interpretation and discussion of raw moments can be difficult, it is trivial here given that any set of raw moments can be expressed as functions of their centered counterparts.[19] As an estimation strategy, we will focus on the second and third raw moments (variance and skewness respectively) suggesting that f in equation 3.5 follow the linear specification in our mean model, equation (3.2) in Section III.

3.6.2 Results

Table 3.3 presents the results for the variance and skewness equations for corn and soybeans. The dependent variable in each model is the yield measure raised to the power of the respective moment then scaled by 10. This is to limit the number of digits in each coefficient and hence can be interpreted as the impact on a tenth of a bushel per acre.[20] Each model is estimated using OLS with standard errors clustered by year. Table 3.3 only includes the fraction irrigated variable and its associated interaction terms. The full complement of regressors and their effects can be found in Table 3.9 in the Appendix. To make the results more intuitive, we include centering adjustments for each parameter, reported in parentheses, to show what effects the raw coefficient has on the central moments.

We find that irrigation is an important conditioning variable across both second and third raw moments. For corn and soybeans alike, marginal land coming under irrigation increases both the raw and centered measures of variance. This may be somewhat odd given that irrigation serves as a tool of risk management. However, when we examine the impact of irrigation on the third raw moment, parameters suggest a positive raw relationship leading to a decrease in centered skewness. This implies that while dispersion is increasing, the distribution is being pulled left (i.e. probability of even lower yields is added). This resembles the distributional impact of self-protection.

Curiously, we find somewhat less intuitive results when examining irrigated land covered under insurance. Insured marginal land exhibits a larger increase in both raw and centered

[19] See [63] chapter 5 pages 146-147 for reference.

[20] This has no bearing on the significance of our results. It is simply done for aesthetic purposes.

Table 3.3: Selected Regression Results for Raw Moments

	$Yield^2$	$Yield^3$
Corn		
Fraction irrigated	256.7^{***}	$3,744.1^{***}$
	(61.4)	$(-1,559.6)$
x fraction insured	59.5^{***}	$1,611.0^{***}$
	(57.7)	$(1,373.75)$
x precipitation	-244.2	$-2,062.5$
	(-555.0)	$(-25,938.9)$
x precipitation^2	102.5	475.3
	(29.0)	(-900.9)
N	3,053	3,053
R^2	0.42	0.37
Mean of dep. var.	167.7	2,402.6
Centered mean of dep. var.	13.2	-9.1
Soybeans		
Fraction irrigated	27.3^{***}	130.8^{***}
	(8.3)	(-60.6)
x fraction insured	13.1^{***}	102.4^{***}
	(11.5)	(56.9)
x precipitation	-46.6^{***}	-231.9^{**}
	(-100.7)	$(-2,057.0)$
x precipitation^2	20.0^{**}	96.3^{*}
	(9.7)	(-30.1)
N	2,820	2,820
R^2	0.35	0.33
Mean of dep. var.	16.4	72.1
Centered mean of dep. var.	1.0	0.0

*Notes: The table above shows results for regressing squared and cubed values of yield on a set of weather, insurance, and irrigation variables. Centered transformations of each raw coefficient are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

variance when irrigated than its uninsured counterparts. Further, the beneficial impacts of irrigation on skewness are diminished quite dramatically when land is also insured. For insured corn, the total change in centered skewness from irrigation is -185.8 compared to uninsured corn -1,559.6. For insured soybeans, the total impact is -3.7 versus -60.6 for uninsured land. This could suggest irrigation is a weak form of self-protection. When

engaging in self-protection, a farmer trades lowered outcome states (the cost of irrigation) for lowered loss probability. Given the results in Table 3.9, the benefits of trade could be small. However, this is speculation as one must consider the risk attitudes of the individual farmer.

3.7 Conclusion

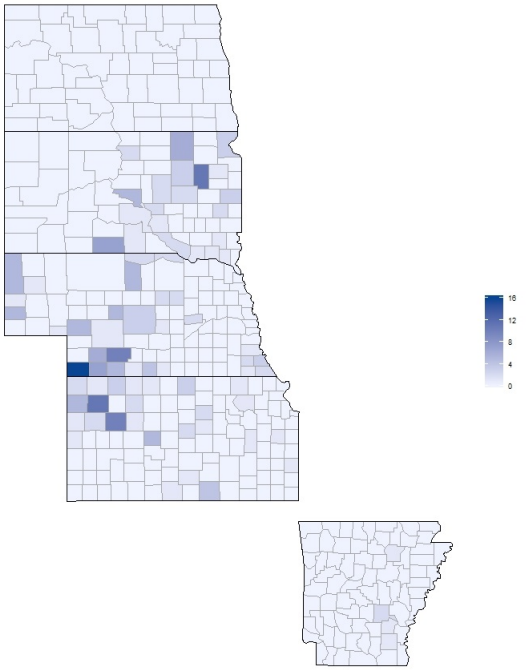
This research finds new evidence regarding the relationship between irrigation and insurance. We estimate the fraction of insured acreage increases the positive benefit of irrigation. We conclude that irrigation acts as a form of self-protection, decreasing the probability of crop loss. In this context, it serves as a complement to traditional market-based crop insurance. We confirm that not only does irrigation increase the average yield, but also increases the variability of yields while skewing the distribution left.

This raises interesting questions regarding the heavy subsidization of crop insurance by the United States government. As policy moves to favor the FCIP as a means to protect farmers, the impacts of irrigation should be considered. If more and more cropland comes under insurance policies, this may lead to increased utilization of irrigation and potentially inefficient uses of water. Coupled with potential magnification from climate change, this could have both financial and environmental impacts not considered in current policy decisions.

We offer in this paper a primary step to understanding the choice farmers have in managing risk inherit to crop production. We present only empirical evidence of how these choices are being made. Ultimately, future research should include risk and decision theory to build a theoretical analysis of the underlying trade-offs.

3.8 Appendix

Figure 3.7: Area Insured Greater than Planted Acreage



Notes: Counties in the sample with the fraction of insured acreage greater than one are listed in blue. The deeper the shade indicates the frequency.

Table 3.4: Regression Results with both Linear and Log-linear Specifications for Corn

	Linear		Log-linear	
	(1)	(2)	(3)	(4)
Fraction irrigated	83.071***	139.745***	0.766***	1.637***
	(2.699)	(8.242)	(0.028)	(0.085)
x fraction insured		13.571***		0.012
		(3.275)		(0.034)
x precipitation		−176.305***		−2.471***
		(25.975)		(0.268)
x precipitation^2		85.716***		1.282***
		(20.649)		(0.213)
Moderate heat	−0.009	0.005	−0.0002***	−0.00000
	(0.006)	(0.008)	(0.0001)	(0.0001)
x fraction insured		−0.008		−0.0001*
		(0.007)		(0.0001)
Extreme heat	−0.260***	−0.178***	−0.003***	−0.002***
	(0.020)	(0.040)	(0.0002)	(0.0004)
x fraction insured		−0.133**		−0.001
		(0.054)		(0.001)
Precipitation	−21.672**	133.561***	−0.228**	1.631***
	(10.930)	(22.251)	(0.114)	(0.229)
x fraction insured		−66.273**		−0.475*
		(27.868)		(0.287)
Precipitation^2	19.845**	−70.024***	0.211***	−0.842***
	(7.711)	(15.681)	(0.081)	(0.162)
x fraction insured		45.599**		0.290
		(21.392)		(0.220)
Fraction insured		34.496***		0.417***
		(11.651)		(0.120)
Time trend	2.013***	1.632***	0.011***	0.010***
	(0.269)	(0.278)	(0.003)	(0.003)
Time trend^2	−0.057***	−0.045***	−0.0004***	−0.0003***
	(0.008)	(0.008)	(0.0001)	(0.0001)
N	3,053	3,053	3,053	3,053
R^2	0.399	0.436	0.353	0.410
Adjusted R^2	0.371	0.405	0.329	0.380

*Notes: The table above shows results for regressing crop-specfic yield on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

Table 3.5: Regression Results with both Linear and Log-linear Specifications for Soybeans

	Linear		Log-linear	
	(1)	(2)	(3)	(4)
Fraction irrigated	19.327***	43.561***	0.524***	1.450***
	(0.876)	(2.918)	(0.026)	(0.085)
x fraction insured		12.605***		0.249***
		(1.099)		(0.032)
x precipitation		−73.574***		−2.476***
		(8.126)		(0.237)
x precipitation^2		32.106***		1.084***
		(5.655)		(0.165)
Moderate heat	0.007***	0.009***	0.0002**	0.0002***
	(0.002)	(0.002)	(0.0001)	(0.0001)
x fraction insured		−0.002		−0.0001*
		(0.002)		(0.0001)
Extreme heat	−0.132***	−0.150***	−0.004***	−0.005***
	(0.010)	(0.018)	(0.0003)	(0.001)
x fraction insured		0.003		0.0004
		(0.024)		(0.001)
Precipitation	21.912***	71.599***	0.509***	2.235***
	(3.358)	(7.459)	(0.098)	(0.217)
x fraction insured		−10.207		−0.432
		(10.108)		(0.295)
Precipitation^2	−11.529***	−39.705***	−0.246***	−1.223***
	(2.075)	(4.899)	(0.061)	(0.143)
x fraction insured		9.473		0.372*
		(7.033)		(0.205)
Fraction insured		−0.633		0.103
		(4.453)		(0.130)
Time trend	−0.239**	−0.256**	−0.003	−0.0001
	(0.121)	(0.121)	(0.004)	(0.004)
Time trend^2	0.009***	0.009***	0.0001	0.00002
	(0.002)	(0.003)	(0.0001)	(0.0001)
N	2,820	2,820	2,820	2,820
R^2	0.266	0.372	0.267	0.374
Adjusted R^2	0.249	0.346	0.249	0.349

*Notes: The table above shows results for regressing crop-specific yield on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

Table 3.6: Regression Results with Additional Weather Controls for Low Heat

	Corn		Soybeans	
	(1)	(2)	(3)	(4)
Fraction irrigated	83.162***	137.194***	19.361***	42.395***
	(2.699)	(8.260)	(0.876)	(2.909)
x fraction insured		16.920***		13.178***
		(3.406)		(1.099)
x precipitation		−174.478***		−71.396***
		(25.924)		(8.092)
x precipitation^2		84.369***		30.432***
		(20.611)		(5.638)
Low heat	−22.536	78.704***	−6.510	45.722***
	(14.241)	(27.614)	(5.280)	(9.223)
x fraction insured		−123.471***		−59.319***
		(31.936)		(10.634)
Moderate heat	−0.004	−0.025**	0.008***	−0.006
	(0.007)	(0.012)	(0.002)	(0.004)
x fraction insured		0.042***		0.018***
		(0.015)		(0.004)
Extreme heat	−0.268***	−0.140***	−0.135***	−0.124***
	(0.021)	(0.042)	(0.010)	(0.019)
x fraction insured		−0.190***		−0.031
		(0.056)		(0.025)
Precipitation	−20.501*	121.190***	21.948***	63.507***
	(10.953)	(22.470)	(3.358)	(7.571)
x fraction insured		−47.710*		−0.476
		(28.215)		(10.210)
Precipitation^2	18.917**	−62.688***	−11.404***	−35.028***
	(7.732)	(15.799)	(2.077)	(4.953)
x fraction insured		35.338		4.300
		(21.513)		(7.067)
N	3,053	3,053	2,820	2,820
R^2	0.399	0.440	0.266	0.379
Adjusted R^2	0.371	0.408	0.249	0.353

*Notes: The table above shows results for regressing crop-specific yield on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

Table 3.7: Regression Results without Weather-Insurance Interaction

	Corn		Soybeans	
	(1)	(2)	(3)	(4)
Fraction irrigated	83.071***	144.042***	19.327***	44.603***
	(2.699)	(8.167)	(0.876)	(2.832)
x fraction insured		5.624**		12.631***
		(2.724)		(0.993)
x precipitation		−165.738***		−77.175***
		(26.054)		(7.641)
x precipitation^2		77.621***		35.388***
		(20.714)		(5.155)
Moderate heat	−0.009	0.001	0.007***	0.008***
	(0.006)	(0.006)	(0.002)	(0.002)
Extreme heat	−0.260***	−0.264***	−0.132***	−0.149***
	(0.020)	(0.020)	(0.010)	(0.009)
Precipitation	−21.672**	89.827***	21.912***	66.798***
	(10.930)	(16.097)	(3.358)	(5.494)
Precipitation^2	19.845**	−40.509***	−11.529***	−35.277***
	(7.711)	(11.183)	(2.075)	(3.610)
Fraction insured		−3.732		−8.096***
		(2.724)		(0.866)
N	3,053	3,053	2,820	2,820
R^2	0.399	0.429	0.266	0.370
Adjusted R^2	0.371	0.399	0.249	0.346

*Notes: The table above shows results for regressing crop-specific yield on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

Table 3.8: Regression Results using Data from 1989-2015

	Corn		Soybeans	
	(1)	(2)	(3)	(4)
Fraction irrigated	89.2***	171.1***	18.4***	46.3***
	(3.8)	(9.9)	(1.2)	(3.8)
x fraction insured		5.5		20.2***
		(4.4)		(1.6)
x precipitation		−245.9***		−97.0***
		(30.8)		(10.3)
x precipitation^2		130.9***		46.4***
		(24.3)		(7.0)
Moderate heat	−0.000**	−0.000	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
x fraction insured		−0.000		−0.000
		(0.000)		(0.000)
Extreme heat	−0.002***	−0.001**	−0.001***	−0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
x fraction insured		−0.002**		0.000
		(0.001)		(0.000)
Precipitation	−27.3**	204.6***	15.1***	70.1***
	(12.9)	(32.9)	(4.1)	(11.0)
x fraction insured		−115.9***		8.1
		(40.3)		(13.7)
Precipitation^2	26.1***	−109.8***	−8.7***	−42.6***
	(9.2)	(23.7)	(2.6)	(7.1)
x fraction insured		72.9**		2.7
		(30.6)		(9.2)
Fraction insured		56.7***		−16.5***
		(16.0)		(5.7)
Time trend	1.9***	1.6***	−0.2	−0.3**
	(0.3)	(0.3)	(0.2)	(0.2)
Time trend^2	−0.05***	−0.04***	0.01*	0.01**
	(0.01)	(0.01)	(0.003)	(0.003)
N	2,264	2,264	2,014	2,014
R^2	0.4	0.4	0.2	0.4
Adjusted R^2	0.3	0.4	0.2	0.3

*Notes: The table above shows results for regressing crop-specific yield on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

Table 3.9: Regression Results for Raw Moments

	Corn		Soybeans	
	(1)	(2)	(3)	(4)
Fraction irrigated	256.7***	3,744.1***	27.3***	130.8***
	(52.3)	(1,131.2)	(5.1)	(35.4)
x fraction insured	59.5***	1,611.0***	13.1***	102.4***
	(20.3)	(476.7)	(2.2)	(18.0)
x precipitation	−244.2	−2,062.5	−46.6***	−231.9**
	(155.4)	(3,296.4)	(13.4)	(93.4)
x precipitation^2	102.5	475.3	20.0**	96.3*
	(115.6)	(2,455.2)	(8.3)	(57.4)
Moderate heat	0.02	0.6	0.01**	0.1**
	(0.04)	(0.9)	(0.003)	(0.02)
x fraction insured	−0.01	0.1	−0.001	−0.003
	(0.04)	(0.9)	(0.003)	(0.02)
Extreme heat	−0.3	−4.7	−0.1***	−0.5**
	(0.2)	(4.2)	(0.04)	(0.2)
x fraction insured	−0.4	−8.4	−0.01	−0.1
	(0.3)	(6.0)	(0.04)	(0.3)
Precipitation	224.5**	2,694.8	47.8***	245.9***
	(107.9)	(2,170.7)	(11.4)	(77.3)
x fraction insured	−176.3	−3,433.5	−1.6	37.6
	(150.8)	(3,343.6)	(19.4)	(132.8)
Precipitation^2	−119.0	−1,420.0	−26.7***	−137.5***
	(72.9)	(1,475.3)	(7.0)	(46.6)
x fraction insured	128.9	2,587.1	2.9	−14.0
	(110.7)	(2,479.2)	(12.4)	(84.5)
Fraction insured	54.5	495.8	−5.2	−65.6
	(73.2)	(1,580.0)	(9.4)	(67.4)
Time trend	5.4**	130.5**	−0.4	−3.3
	(2.2)	(52.0)	(0.3)	(2.1)
Time trend^2	−0.1***	−3.3***	0.01**	0.1**
	(0.1)	(1.2)	(0.01)	(0.05)
N	3,053	3,053	2,820	2,820
R^2	0.4	0.3	0.3	0.3
Adjusted R^2	0.4	0.3	0.3	0.3

*Notes: The table above shows results for regressing crop-specfic yield variations on a set of weather, insurance, and irrigation variables. Standard errors clustered by year are in brackets. Statistical significance at the 0.1, 0.05, and 0.01 levels are denoted by *, **, and *** respectively.*

REFERENCES

[1] Klaus Abbink, Jordi Brandts, Benedikt Herrmann, and Henrik Orzen. Intergroup conflict and intra-group punishment in an experimental contest game. *American Economic Review*, 100:420–447, 2010.

[2] Joshua D Angrist and Alan B Krueger. Empirical strategies in labor economics. *Handbook of labor economics*, 3:1277–1366, 1999.

[3] Francis Annan and Wolfram Schlenker. Federal crop insurance and the disincentive to adapt to extreme heat. *The American Economic Review*, 105(5):262–266, 2015.

[4] John M Antle. Testing the stochastic structure of production: a flexible moment-based approach. *Journal of Business & Economic Statistics*, 1(3):192–201, 1983.

[5] John M Antle. Asymmetry, partial moments, and production risk. *American Journal of Agricultural Economics*, 92(5):1294–1309, 2010.

[6] Kenneth J Arrow. Uncertainty and the welfare economics of medical care. *The American economic review*, pages 941–973, 1963.

[7] Katherine Baicker and Amitabh Chandra. Medicare spending, the physician workforce, and beneficiaries' quality of care. *Health Affairs*, 23(3):291–291, 2004.

[8] Badi H Baltagi, Francesco Moscone, and Elisa Tosetti. Medical technology and the production of health care. *Empirical Economics*, 42(2):395–411, 2012.

[9] Laurie J Bates, Kankana Mukherjee, and Rexford E Santerre. Market structure and technical efficiency in the hospital services industry: A dea approach. *Medical Care Research and Review*, 63(4):499–524, 2006.

[10] Hugo Benitez-Silva and Huan Ni. Health status and health dynamics in an empirical model of expected longevity. *Journal of health economics*, 27(3):564–584, 2008.

[11] Eric Briys and Harris Schlesinger. Risk aversion and the propensities for self-insurance and self-protection. *Southern Economic Journal*, pages 458–467, 1990.

[12] Maurice JG Bun, Teresa D Harrison, et al. Ols and iv estimation of regression models including endogenous interaction terms. *University of Amsterdam Discussion Paper*, 2, 2014.

[13] Amitabh Chandra and Douglas O Staiger. Productivity spillovers in healthcare: evidence from the treatment of heart attacks. *The journal of political economy*, 115:103, 2007.

[14] R.D. Congleton, A.L. Hillman, and K.A. Konrad. *40 Years of Research on Rent Seeking 1: Theory of Rent Seeking*. Springer, 2008.

[15] Paul Contoyannis and Andrew M Jones. Socio-economic status, health and lifestyle. *Journal of health economics*, 23(5):965–995, 2004.

[16] R. Cornes and R. Hartley. Risk aversion, heterogeneity and contests. *Public Choice*, 117:1–25, 2003.

[17] R. Cornes and R. Hartley. Risk aversion in symmetric and asymmetric contests. *Economic Theory*, 51:247–275, 2012.

[18] David Crainich, Louis Eeckhoudt, and Alain Trannoy. Even (mixed) risk lovers are prudent. *American Economic Review*, 103:1529–1535, 2013.

[19] David M Cutler and Adriana Lleras-Muney. Understanding differences in health behaviors by education. *Journal of health economics*, 29(1):1–28, 2010.

[20] Valentino Dardanoni and Adam Wagstaff. Uncertainty and the demand for medical care. *Journal of Health Economics*, 9(1):23–38, 1990.

[21] Cary Deck and Harris Schlesinger. Exploring higher order risk effects. *Review of Economic Studies*, 77:1403–1420, 2010.

[22] Salvatore Di Falco and Jean-Paul Chavas. On crop biodiversity, risk exposure, and food security in the highlands of ethiopia. *American Journal of Agricultural Economics*, 91(3):599–611, 2009.

[23] Joseph J Doyle Jr. Health insurance, treatment and outcomes: using auto accidents as health shocks. *Review of Economics and Statistics*, 87(2):256–270, 2005.

[24] Joseph J Doyle Jr. Returns to local-area healthcare spending: evidence from health shocks to patients far from home. *American economic journal. Applied economics*, 3(3):221, 2011.

[25] Laura Dwyer-Lindgren, Ali H Mokdad, Tanja Srebotnjak, Abraham D Flaxman, Gillian M Hansen, and CJ Murray. Cigarette smoking prevalence in us counties: 1996-2012. *Popul Health Metr*, 12(1):5, 2014.

[26] Sebastian Ebert. Even (mixed) risk lovers are prudent: Comment. *American Economic Review*, 103:1536–1537, 2013.

[27] L. Eeckhoudt and C. Gollier. The impact of prudence on optimal prevention. *Economic Theory*, 26:989–994, 2005.

[28] Louis Eeckhoudt and Harris Schlesinger. Putting risk in its proper place. *American Economic Review*, 96:280–289, 2006.

[29] I. Ehrlich and G.S. Becker. Market insurance, self-insurance, and self-protection. *Journal of Political Econony*, 80:623–648, 1972.

[30] Isaac Ehrlich and Gary S Becker. Market insurance, self-insurance, and self-protection. *Journal of political Economy*, 80(4):623–648, 1972.

[31] Isaac Ehrlich and Hiroyuki Chuma. A model of the demand for longevity and the value of life extension. *Journal of Political Economy*, 98(4):761–82, 1990.

[32] Bichaka Fayissa and Paulos Gutema. Estimating a health production function for sub-saharan africa (ssa). *Applied Economics*, 37(2):155–164, 2005.

[33] Elliott S Fisher, David E Wennberg, Thrse A Stukel, Daniel J Gottlieb, F Lee Lucas, and Etoile L Pinder. The implications of regional variations in medicare spending. part 1: the content, quality, and accessibility of care. *Annals of internal medicine*, 138(4):273–287, 2003.

[34] Elliott S Fisher, David E Wennberg, Thrse A Stukel, Daniel J Gottlieb, F Lee Lucas, and Etoile L Pinder. The implications of regional variations in medicare spending. part 2: health outcomes and satisfaction with care. *Annals of internal medicine*, 138(4):288–298, 2003.

[35] Victor R. Fuchs. The contribution of health services to the american economy. *The Milbank Memorial Fund Quarterly*, 44(4):65–103, 1966.

[36] Victor R Fuchs. *Economic aspects of health*. University of Chicago Press, 1982.

[37] Victor R Fuchs. More variation in use of care, more flat-of-the curve medicine. *Heath Affairs*, 23:VAR–104, 2004.

[38] Titus J Galama, Patrick Hullegie, Erik Meijer, and Sarah Outcault. Is there empirical evidence for decreasing returns to scale in a health capital model? *Health economics*, 21(9):1080–1100, 2012.

[39] Uri Gneezy and Rann Smorodinsky. All-pay auctions–an experimental study. *Journal of Economic Behavior & Organization*, 61:255–275, 2006.

[40] Irving J Good. Maximum entropy for hypothesis formulation, especially for multidimensional contingency tables. *The Annals of Mathematical Statistics*, pages 911–934, 1963.

[41] Michael Grossman. *The demand for health: a theoretical and empirical investigation*. Columbia University Press, 1972.

[42] Michael Grossman. On the concept of health capital and the demand for health. *The journal of political economy*, pages 223–255, 1972.

[43] Andrew Healey, Massimo Mirandola, Francesco Amaddeo, Paola Bonizzato, and Michele Tansella. Using health production functions to evaluate treatment effectiveness: an application to a community mental health service. *Health economics*, 9(5):373–383, 2000.

[44] Arye L. Hillman and Eliakim Katz. Risk-averse rent seekers and the social cost of monopoly power. *Economic Journal*, 94:104–110, 1984.

[45] Ronaldl Horswell and Stephenw Looney. Diagnostic limitations of skewness coefficients in assessing departures from univariate and multivariate normality: Diagnostic limitations of skewness coefficients. *Communications in statistics-simulation and computation*, 22(2):437–459, 1993.

[46] Daniel Houser and Thomas Stratmann. Gordon tullock and experimental economics. *Public Choice*, 152:211–222, 2012.

[47] Eliot A Jamison, Dean T Jamison, and Eric A Hanushek. The effects of education quality on income growth and mortality decline. *Economics of Education Review*, 26(6):771–788, 2007.

[48] Edwin T Jaynes. Information theory and statistical mechanics. *Physical review*, 106(4):620, 1957.

[49] Paan Jindapon. Do risk lovers invest in self protection? *Economics Letters*, 121:290–293, 2013.

[50] Paan Jindapon and William S Neilson. Higher-order generalizations of arrow–pratt and ross risk aversion: A comparative statics approach. *Journal of Economic Theory*, 136(1):719–728, 2007.

[51] Donald S Kenkel. Should you eat breakfast? estimates from health production functions. *Health economics*, 4(1):15–29, 1995.

[52] M. Kimball. Precautionary savings in the small and in the large. *Econometrica*, 58:53–73, 1990.

[53] K. Konrad and H. Schlesinger. Risk aversion in rent seeking and rent augmenting games. *Economic Journal*, 107:1671–1683, 1997.

[54] Kai A. Konrad. *Strategy and Dynamics in Contests*. Oxford University Press, 2009.

[55] Wooyoung Lim, Alexander Matros, and Theodore L. Turocy. Bounded rationality and group size in tullock contests: Experimental evidence. *Journal of Economic Behavior & Organization*, 99:155–167, 2014.

[56] Adriana Lleras-Muney. The relationship between education and adult mortality in the united states. *The Review of Economic Studies*, 72(1):189–221, 2005.

[57] Grace Lordan, Eliana Jimenez Soto, Richard PC Brown, and Ignacio Correa-Valez. Socioeconomic status and health outcomes in a developing country. *Health economics*, 21(2):178–186, 2012.

[58] Stephen Martin, Nigel Rice, and Peter C Smith. Does health care spending improve health outcomes? evidence from english programme budgeting data. *Journal of health economics*, 27(4):826–842, 2008.

[59] Robert Mendelsohn, William D Nordhaus, and Daigee Shaw. The impact of global warming on agriculture: a ricardian analysis. *The American economic review*, pages 753–771, 1994.

[60] C. Menezes, C. Geiss, and J. Tressler. Increasing downside risk. *American Economic Review*, 70:921–932, 1980.

[61] Olena Y Nizalova and Irina Murtazashvili. Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, 5(1):71–77, 2016.

[62] Charles Noussair, Stefan Trautmann, and Gijs Van de Kuilen. Higher order risk attitudes, demographics, and financial decisions. *Review of Economic Studies*, 81:325–355, 2014.

[63] Athanasios Papoulis and S Unnikrishna Pillai. *Probability, random variables, and stochastic processes*. Tata McGraw-Hill Education, 2002.

[64] J.E. Pečarić, F. Proschan, and Y.L. Tong. *Convex Functions, Partial Orderings, and Statistical Applications*. Academic Press, 1992.

[65] Brennan C. Platt, Joseph Price, and Henry Teppan. The role of risk preferences in pay-to-bid auctions. *Management Science*, 59:2117–2134, 2013.

[66] C. J. Ruhm. Are recessions good for your health?,. *Quarterly Journal of Economics*, 115:617–50, 2003.

[67] Christopher J Ruhm. Healthy living in hard times. *Journal of health economics*, 24(2):341–363, 2005.

[68] Wolfram Schlenker, W Michael Hanemann, and Anthony C Fisher. The impact of global warming on us agriculture: an econometric analysis of optimal growing conditions. *Review of Economics and Statistics*, 88(1):113–125, 2006.

[69] Wolfram Schlenker and Michael J Roberts. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598, 2009.

[70] Johannes Schoder and Peter Zweifel. Flat-of-the-curve medicine: a new perspective on the production of health. *Health economics review*, 1(1):1–10, 2011.

[71] James W Shaw, William C Horrace, and Ronald J Vogel. The determinants of life expectancy: an analysis of the oecd health data. *Southern Economic Journal*, pages 768–783, 2005.

[72] Roman Sheremeta. Overbidding and heterogeneous behavior in contest experiments. *Journal of Economic Survey*, 27:491–514, 2013.

[73] James Alexander Shohat and Jacob David Tamarkin. *The problem of moments*. Number 1. American Mathematical Soc., 1943.

[74] Jonathan S Skinner, Douglas O Staiger, and Elliott S Fisher. Is technological change in medicine always worth it? the case of acute myocardial infarction. *Health affairs*, 25(2):w34–w47, 2006.

[75] F. Szidarowszky and K. Okuguchi. On the existence and uniqueness of pure nash equilibrium in rent-seeking games. *Games and Economics Behavior*, 18:135–140, 1997.

[76] Jesse Tack, Ardian Harri, and Keith Coble. More than mean effects: Modeling the effect of climate on the higher order moments of crop yields. *American Journal of Agricultural Economics*, page aas071, 2012.

[77] M Tarazona-Gomez. Are individuals prudent? an experimental approach using lotteries. *University of Toulouse Working Paper*, 2004.

[78] James Thornton. Estimating a health production function for the us: some new evidence. *Applied Economics*, 34(1):59–62, 2002.

[79] James A Thornton. Does more medical care improve population health? new evidence for an old controversy. *Applied Economics*, 43(24):3325–3336, 2011.

[80] James A Thornton and Jennifer L Rice. Determinants of healthcare spending: a state level analysis. *Applied Economics*, 40(22):2873–2889, 2008.

[81] N. Treich. Risk-aversion and prudence in rent-seeking games. *Public Choice*, 145:339–349, 2010.

[82] G. Tullock. Efficient rent-seeking. In J. M. Buchanan, R. D. Tollison, and G. Tullock, editors, *Toward a Theory of the Rent-seeking Society*. Texas A & M University Press, 1980.

[83] Gordon Tullock. On the efficient organization of trials. *Kyklos*, 28:745–762, 1975.

[84] Christopher A Whaley. Beyond average health: higher moments of the health production function. *Working Paper*, 2016.

[85] Ximing Wu. Calculation of maximum entropy densities with application to income distribution. *Journal of Econometrics*, 115(2):347–354, 2003.

[86] T. Yamazaki. The uniqueness of pure-strategy nash equilibrium in rent-seeking games with risk-averse players. *Public Choice*, 139:335–342, 2009.