Does Crop Insurance Inhibit Climate-Change Irrigation-Technology Adaption?

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Introduction

Historically, U.S. Midwest agricultural production has established a balance with annual mean precipitation and water demand (Lobell et al., 2014). An example is the mitigation of any potential spring excess precipitation with artificial drainage for timely fieldwork and aeration. With climate change, the increased volatility of precipitation and its effect on crop yield may inhibit this balance. Rainfall may not consistently occur when required, leading to enhanced periods of excess precipitation accompanying summer water deficits, which may negatively affect corn and soybean yields (Lobell et al., 2014; Ort and Long, 2014; Walthall et al., 2012). Researchers project such variable precipitation caused by climate change to continue (Karl, 2010).

Adapting agricultural practices to climate change is a challenging process. Climate change adaptations may not occur because of limited incentives, market failure, diminishing marginal effects, maladaptation, differential returns, skepticism, and limited resources ((Barnett and O'Neill, 2010; Glantz, 1988; McCarl et. al., 2016; Parry et. al., 2009; Rejesus et. al., 2013). In contrast, there are producers who are already taking climate-change adaption steps including conservation practices, crop insurance, climate-change mitigation technology, diversification, and switching to alternative enterprises (Mase et. al. 2016).

Although these options exist, producers face many hurdles in adoption. Research indicates technology investment will not occur unless sunk costs are less than the expected present value by a large hurdle rate. As an example, producers tend to wait until a random event, such as a drought, which creates significantly higher marginal returns, before investing in irrigation (Carey and Zilberman, 2002). Such investment decisions do not exist in isolation.

Schoengold et al. (2014) find a producer who receives disaster and indemnity payments is less likely to invest in conservation tillage practices.

One technology that may help mitigate the risk of increased precipitation volatility is drainage water recycling (DWR). This technology involves diverting subsurface drainage water into on-farm ponds and storing drained water for later irrigation. While implementing this technology is one possible solution to climate-change risk, there are hurdles to implementation. The sunk cost and uncertainty of the technology coupled with producer perception and alternative mitigating practices such as crop insurance all play a role in DWR adoption.

The objective is to estimate these possible hurdles, specifically crop insurance, to DWR adoption. This estimation employs real options analysis to find the revenue triggers, which will incent investment in DWR with and without the presence of crop insurance. By comparing the two revenue triggers, the analysis will evaluate the extent that crop insurance is interfering with DWR adoption. Sensitivity analysis, including adding different levels of a government subsidy to DWR and crop insurance, indicates how policy changes affect DWR adoption. These revenue triggers and intervals can be used to provide decision makers a monetary indication of the degree government mechanisms will influence DWR adoption.

In addition to DWR, the following are other technology options for mitigating climate change:

New crop varieties,
Early warning weather systems,
Water management innovations,
Policies and programs to influence land and water resource use,
Crop and livestock type and variety diversification,
Intensification of production,
Location of crop and livestock production,

Alternative fallow and tillage practices,

Irrigation, and

Timing of production operations (Smit and Skinner, 2002).

Federal crop insurance may play a role in the feasible adoption of these technologies. The insurance can have a spillover (secondary or collateral) effect on mitigating yield and revenue losses from climate change. Producers can choose between two types of crop insurance: yield or revenue protection. The coverage levels vary within plans from 50 to 85% coverage. The subsidy decreases as the coverage level increases, so a higher coverage level results in more out-of-pocket cost for producers. Many lenders require producers to purchase federal crop insurance. The insurance reduces producers' net-return volatility, which could interfere with market solutions to address precipitation-pattern changes such as DWR. However, the adoption of a new technology also depends on the economic and geographic feasibility of the project. The problem is government subsidized crop insurance may be interfering with DWR adoption.

Crop Insurance

Within Indiana, the most common crop-insurance policy purchased is Revenue Protection (RP) insurance, which currently accounts for 85% of the total crop insurance policies sold. In 2018, RP Indiana policies totaled more than 23,000; insuring a total of 3.75 million acres (RMA Summary of Business Reports and Data, 2018). RP insurance, first administered by the Risk Management Agency (RMA) in 2011, ensures producers receive a certain level of revenue per acre instead of a payment solely based on yield or price (Plastina and Edwards, 2014).

In Indiana, the minimum coverage level for RP insurance is 50% of revenue with 5% increments up to a maximum coverage level of 85% (RMA Summary of Business Reports and Data, 2018). The unit structure of crop insurance determines how to group acreage. Producers can elect to insure their acres by basic, optional, or enterprise unit coverage. The basic unit structure allows for the combined insurance of owned and cash rented acres for a single crop, which is combining all of the crop units. Optional separates units of a single crop by type or practice. For example, a producer may want to use an optional unit to separate owned and cash rented land or irrigated and non-irrigated land. The enterprise unit structure allows for the combination of all acres of the same crop in the same county. To qualify for enterprise units, the insured acreage must qualify for two or more basic units or two or more optional units. The basis for the yield calculation for RP insurance is the Actual Production History (APH) of each unit of the farm insured. To calculate an APH yield, the insurance unit must have a minimum of three years and a maximum of ten years of production history. If the minimum of three years of records are not available for the unit, RMA allows the substitution of a Transition (T) yield for the missing data. The basis for the T yield is the 10-year historical county average yield (Plastina and Edwards, 2017).

The U.S. Bureau of Land Management divides property using the Public Land Survey System (PLSS). The typical division of each county is into 16 townships and the division of townships is into 36 sections. To qualify for enterprise by practice, a producer must have at least 20% of the insured crop acreage in this practice in a separate section. As an example, a producer would not qualify for enterprise by practice if they only have one irrigated field. They would require at least one other irrigated field in a separate section from the irrigated field, which is greater than, or equal to 20% of the producer's insured crop acreage in the enterprise unit. In addition, if a producer switches to enterprise by practice, they are required to move their insurance coverage on irrigated acres down a minimum of one level. For example, if a producer had 85% coverage RP insurance in enterprise units and wanted to switch to enterprise by practice units, they would be required to move down to 80% coverage on the irrigated acres (Cole, 2018).

Literature Review

The literature varies on the magnitude crop insurance interferes with the adoption of conservation practices and new agricultural technologies. Schoengold et al. (2014) indicate recent disaster and indemnity payments are associated with a decrease in the use of conservation till and an increase in the use of no-till. Smith and Goodwin (1996) find producers who purchase crop insurance tend to use fewer chemical inputs due to moral-hazard incentives. Horowitz and Lichtenberg (1993) find federally insured farms apply more nitrogen and spend more on pesticides than uninsured producers. Babcock and Hennessy (1996) find crop insurance will lead to minor reductions in applications of nitrogen if the coverage levels are at or below 70% of mean yield or revenue. There is some disagreement among the literature on the overall effect of crop insurance on agricultural inputs. Woodard et al. (2012) find crop insurance rules have incentive-distorting impacts, which disincentivize the adoption of skip-row planting. Dalton et al. (2004) find federal crop insurance programs are inefficient at reducing weather-related production risk in humid regions, and the risk management benefits from implementing a supplemental irrigation system depend on the technology and scale of the system. Without a clear consensus on the effect of crop insurance on technology adoption, a literature gap exists in determining the level of crop insurance and technology subsidies required for adoption. The question lacking an answer is the level of subsidies triggering adoption.

Implementing a DWR system is a major investment decision, which requires consideration of the interactions among investment uncertainty, irreversibility, and timing. For such consideration real options analysis offers a method, which incorporates the option value of waiting for future information. In terms of agriculture and energy, Price and Wetzstein (1999) explore irreversible investment decisions in perennial crops with yield and price correlated stochastic processes. In forestry, numerous articles employ real options in investigating optimal rotation, investment timing, and value of timber cutting contracts (Chaudhari et. al. 2016). For energy investments, real options methods consider ethanol plant investment, co-firing coal with wood pellets for electricity generation, and biodiesel investment in a disruptive tax-credit policy environment (Gonzalez et al., 2012; Stutzman et al., 2017; Liu et al., 2018). Building on this literature, the objective is to develop a real options model for the adoption of DWR considering the disruptive crop-insurance policies. This will further the understanding of the degree crop insurance influences the adoption of DWR.

Conceptual Framework

Stochastic Yield and Price

The stochastic nature of price, p, and yield, q, may be represented by geometric Brownian motion processes

$$dp = \alpha_p p dt + \sigma_p p dz_p,$$

$$dq = \alpha_q q dt + \sigma_q q dz_q,$$

where dp and dq represent the change in the per-bushel price and yield of corn, respectively, α is the rate of change or drift rate, σ is the standard deviation or volatility. The increment of a Wiener process is dz, with $E\left(dz_p^2\right) = E\left(dz_q^2\right) = dt$ and $E\left(dz_p dz_q\right) = \rho_R dt$, where ρ_R denotes the correlation coefficient between p and q. Following Price and Wetzstein (1999), letting revenue be $R = pq$, the stochastic process of revenue is then

$$dR = \alpha_R R dt + \sigma_R R dz_R,$$

where $\alpha_R = \alpha_p + \alpha_q + \rho_R \sigma_p \sigma_q$ and $\sigma_R = (\sigma_p^2 + \sigma_q^2 + 2\rho_R \sigma_p \sigma_q)^{1/2}$.

Let the returns in period *t* with and without DWR be R_D and R_C, respectively. Allowing both price and yield to fluctuate randomly, two correlated geometric Brownian motion processes result

$$dR_C = \alpha_C R_C dt + \sigma_C R_C dz_C \ , \tag{1a}$$

$$dR_D = \alpha_D R_D dt + \sigma_D R_D dz_D \ , \tag{1b}$$

where α_C and α_D are associated with α_R, and σ_C and σ_D are associated with σ_R. The increment of a Wiener process is *dz* with the properties $E(dz_C^2) = E(dz_D^2) = dt$ and $E(dz_C dz_D) = \rho dt$, where ρ is the correlation coefficient between the uncertainties incorporated in the change of the two revenues.

The Role of Crop Insurance

The availability of crop insurance results in producer's returns jumping when faced with a crop disaster. The effect is Poisson type policy jump on DWR adoption, investigated with the theory of investment under uncertainty. Let θ represent federal crop insurance with $\lambda_1 dt$ denoting the probability it will be implemented in the next interval of time, *dt* and $\lambda_0 dt$ the probability it will be withdrawn. As assumed, producers are price takers. Following closely Dixit and Pindyck (1994) along with Lin and Huang (2010, 2011), the theory assumes a producer is considering adopting DRW with sunk cost of *I*.

It is further assumed over an interval of low returns say $(0, R_D^1)$, DWR will not be adopted regardless if there is crop insurance or not. Over the interval $(R_D^1,\ R_D^0)$, DWR will be adopted if there is no crop insurance, but the producer will wait if there is crop insurance with the possibility of it being withdrawn. Beyond R_D^0 the prospect of immediate revenues will be so large, the producer will adopt DWR regardless if there is crop insurance or not. As illustrated in

Figure 1, interest is in determining the trigger returns R_D^1 and R_D^0, relative to R_C, where within this revenue interval no crop insurance is effective in stimulating DWR adoption.

Interval (R_D^0, ∞): Adopt DWR

Over the range *(R_D^0, ∞)*, the dominant strategy is to always adopt DWR regardless if there is crop insurance or not. The value of the investment opportunity is then

$$V^0(R_D - R_C) = \frac{R_D}{r-\alpha_D} - \frac{R_C}{r-\alpha_C} - \frac{v}{r} - I, \tag{2a}$$

in the absence of crop insurance and

$$V^1(R_D - R_C) = \frac{R_D}{r-\alpha_D} - \frac{R_C}{r-\alpha_C} - \frac{v-\theta}{r} - I, \tag{2b}$$

with crop insurance. Refer to Appendix A for the derivation of Equation (2a), where r is the discount rate, *v* and *I* are the variable and sunk costs of adopting DWR, respectively, and $\theta < 0$ is the decline in expected net insurance payout, payout minus premium, from adopting DWR.

Interval (R_D^1, R_D^0): Disruptive Crop Insurance

In contrast, over the range *(R_D^1, R_D^0)*, with no crop insurance, DWR is adopted and with it is not. Adoption without crop insurance is the same as (2a) and with, $V^1(R_D - R_C)$ is determined as follows. In the next time interval, dt, crop insurance will be withdrawn with probability $\lambda_0 dt$ and DWR adopted with value $V^0[R_D - R_C + d(R_D - R_C)]$. DWR adoption will not occur with crop insurance, yielding a value of $V^1[R_D - R_C + d(R_D - R_C)]$. This yields

$$V^1(R_D, R_C) = e^{-rdt}\{\lambda_0 dt E V^0[R_D - R_C + d(R_D - R_C)]$$
$$+ (1 - \lambda_0 dt) E V^1[R_D - R_C + d(R_D - R_C)]\},$$

where *E* is the expectation operator. This is the probability of insurance being withdrawn times the value of DWR plus the probability of no withdraw of insurance times the value of no DWR.

The Bellman equation yielding the optimal timing for DWR adoption with crop insurance (waiting to invest) is

$$E[dV^1(R_D - R_C)] = \{rV^1[R_D - R_C] - \lambda_0[V^0[R_D - R_C] - V^1[R_D - R_C]]\}dt\,, \tag{3}$$

where over the time interval dt the expected rate of capital appreciation, $dV^1[R_D - R_C]$, is equal to the total expected return, the right-hand side of (3). This total expected return is the discount rate r times the investment value with crop insurance mitigated by the expected capital gain from doing away with crop insurance in the immediate future, the last term in (3).

Expanding the left-hand-side of (3) by employing Ito's Lemma and substituting (1) results in

$$E[dV^1[R_D - R_C]] = \alpha_C R_C V_C^1 + \alpha_D R_D V_D^1 + \frac{1}{2}(V_{CC}^1 \sigma_C^2 R_C^2 + 2\rho V_{CD}^1 \sigma_C \sigma_D R_D R_C + V_{DD}^1 \sigma_D^2 R_D^2)dt,$$

where $V_i^1 = \frac{\partial V^1}{\partial R_i}$ and $V_{ij}^1 = \frac{\partial^2 V^1}{\partial R_i R_j}$, i, $j = D,C.$

The Bellman equation (3) is then

$$\frac{1}{2}(V_{CC}^1 \sigma_C^2 R_C^2 + 2\rho V_{CD}^1 \sigma_C \sigma_D R_D R_C + V_{DD}^1 \sigma_D^2 R_D^2) + \alpha_C R_C V_C^1 + \alpha_D R_D V_D^1 - rV^1 + \lambda_0[V^0 - V^1] = 0. \tag{4}$$

The last term captures the expected capital gain from a withdraw of crop insurance in the immediate future. This is a partial differential equation with a free-boundary condition. As noted by Dixit and Pindyck (1994), analytical solutions are rare with numerical solutions generally only tailored for a particular problem. For this problem, a solution is possible by exploiting its homogeneity nature, which reduces it to one dimension. If the returns for DWR adoption and nonadoption are double, then the value of the investment will also double. The optimal decision then depends the ratio $\omega = \frac{R_D}{R_C}$. This yields expression

$$V^i(R_D - R_C) = R_C f^i\left(\frac{R_D}{R_C}\right) = R_C f^i(\omega), i = 0, 1.$$

The partial differentiations are then

$$V_D^i = f_\omega^i(\omega),\ V_C^i = f(\omega) - \omega f_\omega^i(\omega),$$

$$V_{DD}^{i} = \frac{f_{\omega\omega}^{i}(\omega)}{R_C},\ V_{DC}^{i} = -\frac{\omega f_{\omega\omega}^{i}(\omega)}{R_C},$$

$$V_{CC}^{i} = \frac{\omega^2 f_{\omega\omega}^{i}(\omega)}{R_C},\ \text{i} = 0, 1. \tag{5}$$

Substituting (5) into (4) and rearranging

$$\frac{1}{2}(\sigma_C^2 - 2\rho\sigma_C\sigma_D + \sigma_D^2)\omega^2 f_{\omega\omega}^{1}(\omega) + (\delta_C - \delta_D)\omega f_{\omega}^{1}(\omega) - \delta_C f^1(\omega) + \lambda_0[f^0(\omega) - f^1(\omega)] = 0, \tag{6a}$$

where $\alpha_i = r - \delta_i$, and $f_{\omega}^{1}(\omega) = \frac{\partial f^1}{\partial \omega}$ and $f_{\omega\omega}^{1}(\omega) = \frac{\partial^2 f^1}{\partial \omega^2}$.

Solving (6a) yields

$$f^1(\omega) = A_1\omega^{\beta_1} + A_2\omega^{\beta_2} + \frac{\lambda_0\omega}{\delta_D(\delta_D+\lambda_0)} - \frac{\lambda_0(\frac{1}{\delta_C}+\frac{v}{rR_C}+\frac{I}{R_C})}{\delta_C+\lambda_0}, \tag{6b}$$

where A_1 and A_2 are constants and β_1 and β_2 are the positive and negative characteristic roots of the quadratic equation

$$\tfrac{1}{2}\sigma^2\beta(\beta - 1) + (\delta_C - \delta_D)\beta - (\delta_C + \lambda_0) = 0,$$

where $\sigma^2 = \sigma_C^2 - 2\rho\sigma_C\sigma_D + \sigma_D^2$.

Interval $(0,R_D^1)$: Wait to Adopt DWR

In the final range $(0,R_D^1)$, the decision to adopt DWR is postponed regardless of if there is crop insurance or not. Over this range, the differential equation for determining when to adopt DWR with crop insurance is (6a). Similarly, given no crop insurance, the differential equation for determining when to adopt DWR is

$$\frac{1}{2}(\sigma_C^2 - 2\rho\sigma_C\sigma_D + \sigma_D^2)\omega^2 f_{\omega\omega}^{0}(\omega) + (\delta_C - \delta_D)\omega f_{\omega}^{0}(\omega) - \delta_C f^0(\omega) + \lambda_1[f^1(\omega) - f^0(\omega)] = 0. \tag{7}$$

As demonstrated by Dixit and Pindyck (1994), (6a) and (7) yield solutions to the differential equations for the range $(0,R_D^1)$

$f^1(\omega) = (\lambda_0\lambda_1 G\omega^{\beta_a} + \lambda_0 H\omega^{\beta_s})/(\lambda_0 + \lambda_1)$, (8a)

$f^0(\omega) = (\lambda_0\lambda_1 G\omega^{\beta_a} - \lambda_1 H\omega^{\beta_s})/(\lambda_0 + \lambda_1)$, (8b)

where β_a and β_s are roots of quadratic equations (see Appendix B) with G and H parameters.

<u>Solving the System of Equations – Value Matching and Smoothing Pasting Conditions</u>

At the trigger R_D^1, there will be DWR adoption with no crop insurance, which leads to equality of (2a) and (8b) yielding the following value-matching and smooth-pasting conditions

$(\lambda_0\lambda_1 G(\omega^1)^{\beta_a} - \lambda_1 H(\omega^1)^{\beta_s})/(\lambda_0 + \lambda_1) = \frac{\omega^1}{r-\alpha_D} - \frac{1}{r-\alpha_C} - \frac{v}{rR_C} - \frac{I}{R_C}$, value matching, (9a)

$(\lambda_0\lambda_1\beta_a G(\omega^1)^{\beta_a-1} - \lambda_1\beta_s H(\omega^1)^{\beta_s-1})/(\lambda_0 + \lambda_1) = 1/\delta_D$, smooth pasting, (9b)

where $\omega^1 = R_D^1/R_C$.

For the R_D^0 trigger, the conditions are the equality of (6b) and (2b), yielding

$A_1(\omega^0)^{\beta_1} + A_2(\omega^0)^{\beta_2} + \frac{\lambda_0\omega^0}{\delta_D(\delta_D+\lambda_0)} - \frac{\lambda_0(\frac{1}{\delta_C}+\frac{v}{rR_C}+\frac{I}{R_C})}{\delta_C+\lambda_0} = \frac{\omega^0}{r-\alpha_D} - \frac{1}{r-\alpha_C} - \frac{v-\theta}{rR_C} - \frac{I}{R_C}$, value matching,

(9c)

$A_1\beta_1(\omega^0)^{\beta_1-1} + A_2\beta_2(\omega^0)^{\beta_2-1} + \frac{\lambda_0}{\delta_D(\delta_D+\lambda_0)} = 1/\delta_D$, smooth pasting, (9d)

where $\omega^0 = R_D^0/R_C$.

Following Dixit and Pindyck (1994), the last conditions are the equality of (6b) and (8a), yielding

$(\lambda_0\lambda_1 G(\omega^1)^{\beta_a} + \lambda_0 H(\omega^1)^{\beta_s})/(\lambda_0 + \lambda_1) = A_1(\omega^1)^{\beta_1} + A_2(\omega^1)^{\beta_2} + \frac{\lambda_0\omega^1}{\delta_D(\delta_D+\lambda_0)} - \frac{\lambda_0(\frac{1}{\delta_C}+\frac{v}{rR_C}+\frac{I}{R_C})}{\delta_C+\lambda_0}$,

(9e)

$(\lambda_0\lambda_1\beta_a G(\omega^1)^{\beta_a-1} + \lambda_0\beta_s H(\omega^1)^{\beta_s-1})/(\lambda_0 + \lambda_1) = A_1\beta_1(\omega^1)^{\beta_1-1} + A_2\beta_2(\omega^1)^{\beta_2-1} + \frac{\lambda_0}{\delta_D(\delta_D+\lambda_0)}$.

(9f)

The six equations in (9) are solved numerically for the two triggers, R_D^0 and R_D^1, and the four parameters A_1, A_2, G, and H.

Data and Estimation Procedure

Yield and Price Data

The Variable Infiltration Capacity (VIC) model with the CropSyst crop simulation model simulate estimates for future (2041-2070) irrigated and non-irrigated west-central Indiana yield (Bowling et. al, 2018). Figures 2 and 3 display the non-irrigated and irrigated detrended yield data. CropSyst also provides non-irrigated and irrigated yield data for the historic period (1984-2013). Figures 4 and 5 display detrended historical yield data.

The source for the historical Indiana price data for the years 1984-2013 is the NASS Quick Stats website (NASS, 2018). The corn commodity PPI from the U.S. Bureau of Labor Statistics adjusts historical prices in terms of 2017 prices. Figure 6 displays adjusted historical Indiana corn prices from 1984-2013. For each year, multiplication of adjusted price and historic yield provides non-irrigated and irrigated revenues.

Unit Root Analysis

The assumption is price and yield follow a stochastic process represented by geometric Brownian motion. For determining whether or not the processes have unit roots (follow a geometric Brownian motion), consider the augmented Dickey-Fuller (ADF) test

H_0: The data series contains a unit root.

H_a: The data series is stationary.

Model selection employs the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Results indicate yield and price are represented by an AR(1) process. Table 1 lists the results of the ADF test applied to deflated price and detrended irrigated and non-irrigated yield. The ADF test fails to reject the null hypothesis that the data series contain a unit root for both price and yield data.

Cost Data

Assume the west-central Indiana landscape entails an impounded-pond system, requiring no excavation with a field size of 80 acres. The assumed irrigation type is center pivot. The sunk cost includes the construction, land, pivot, and pumping plant costs. The variable cost includes the annual land cost, electricity, and labor (Reinhart and Frankenberger, 2018). Table 2 displays sunk and variable costs by category.

Crop Insurance Data

The parameter Θ represents the decline in expected net insurance payout from adopting DWR. With the adoption of DWR, producers would generally switch their RP insurance units from enterprise to enterprise by practice (Cole, 2018). This would allow the separation of irrigated and non-irrigated fields. Despite the separation of irrigated fields for RP insurance, the magnitude and direction of the expected net crop insurance payout from adopting DWR is ambiguous. The expected net insurance payout may increase or decline depending on the change in premium and expected indemnity. If producers switch from enterprise to enterprise by practice, their premiums will decrease given the imposed step down in coverage level. However, by how much the premium will decline is ambiguous given dependence on the initial coverage and the actual change in coverage level following the implementation of DWR. Also, not all producers may start out in enterprise units. With basic or optional units, a move to enterprise by practice would also realize a reduction in premiums from higher premium subsidies associated with enterprise units relative to basic or optional units. A move from basic or optional units to enterprise units would also affect revenue guarantees and thus expected indemnities. In addition, the reduced yield risk and increased APH associated with DWR influence expected indemnity reduction. However, a necessary lag in realizing these benefits would result from the requirement to build up a minimum of three-years APH. During this lag, the change in expected indemnity would depend on the productivity of the farm relative to the average productivity of county irrigated acreage. If the farm is more productive than the average county irrigated acreage, this would decrease the farm's APH and increase the expected indemnity. If the farm is less productive than the average county irrigated acreage, this would increase the farm's APH and reduce the expected indemnity. In summary, if the decline in premium the producer pays is greater than the change in the expected indemnity, then Θ is positive. If the decrease in premium the producer pays is less than the change in the expected indemnity, then Θ is negative. The specific value of Θ is indeterminate and influenced by the net change in premiums and indemnity.

Estimation Procedure

Table 3 displays the baseline parameter values. Follwing Dixit and Pindyck (1994), the assumption is price and yield follow geometric Brownian motion, and their logarithms follow a simple Brownian motion

$$d(lnx) = \left(\alpha - \frac{1}{2}\sigma^2\right)dt + \sigma dz.$$

where $d(lnx)$ follows a normal distribution with mean μdt and variance $\sigma^2 dt$ over a finite time interval t. Absolute changes in x, Δx, are lognormally distributed.

For the first difference of the logarithm of historical prices, non-irrigated and irrigated future yield, the drift (μ) and volatility (σ) are estimated by applying the maximum likelihood method to the simple Brownian motion equation

$$\hat{\mu} = \bar{\gamma} = \frac{1}{n}\sum_{t=1}^{n} \gamma_t,$$

$$\hat{\sigma} = std\ (\gamma_t) = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (\gamma_t - \hat{\mu})^2}\ .$$

where n is the number of observations and $\gamma_t = \Delta x_t / x_t$. The estimate for drift is:

$$\hat{\alpha} = \hat{\mu} + \frac{1}{2}\hat{\sigma}^2.$$

These formulas are used to estimate price drift (α_p), price volatility (σ_p), conventional yield drift (α_C), conventional yield volatility (σ_C), DWR yield drift (α_D), and DWR yield volatility (σ_D).

The parameter (ρ_C) is the correlation between price and historical conventional yield, and the parameter (ρ_D) is the correlation between price and historical irrigated yield. The conventional revenue drift (α_{RC}) and volatility (σ_{RC}) are

$$\alpha_{RC} = \alpha_p + \alpha_C + \rho_C \sigma_C \sigma_p,$$

$$\sigma_{RC} = \sqrt{\sigma_p{}^2 + \sigma_C{}^2 + 2\rho_C \sigma_p \sigma_C}\ .$$

Similarly, DWR revenue drift (α_{RD}) and volatility (σ_{RD}) are

$$\alpha_{RD} = \alpha_p + \alpha_D + \rho_D \sigma_D \sigma_p,$$

$$\sigma_{RD} = \sqrt{\sigma_p{}^2 + \sigma_D{}^2 + 2\rho_D\sigma_p\sigma_D} \ .$$

The correlation coefficient between the uncertainty incorporated in the change of the two revenues (ρ_R) is the correlation between DWR and conventional revenue. The formula calculates an overall revenue volatility (σ_R)

$$\sigma_R = \sigma_{RC}^2 - 2\rho_R\sigma_{RC}\sigma_{RD} + \sigma_{RD}^2.$$

The model assumes a risk-free interest rate (r) of 5%. The calculation of per acre variable (V) and sunk (I) costs of adopting DWR assume a cost scenario of a west-central Indiana impounded system on an 80 acre field with an electric powered center pivot irrigation system. The survey results of farmers about crop insurance are not yet available, so assumptions are made for the probability crop insurance will not be implemented in the next time interval (λ_0) and the probability crop insurance will be implemented in the next time interval (λ_1) based on current expectations of the survey results. The change in expected net insurance payout from adopting DWR (θ) is assumed as $\theta = 0$ for this analysis. Multiplying 2017 yield and price results in a value for conventional revenue (R_C). The difference between the expected rate of return and the expected capital gain with no DWR (δ_C) is $\delta_C = r - \alpha_{RC}$, and the difference between the expected rate of return and the expected capital gain with DWR (δ_D) is $\delta_D = r - \alpha_{RD}$.

Results

As illustrated in Figure 7, results from the model indicate values of $\omega_0 = 1.36$ and $\omega_1 = 1.36$ where $\omega^0 = R_D^0/R_C$ and $\omega^1 = R_D^1/R_C$. These ratios result in a revenue threshold of $882 per acre with crop insurance and without crop insurance. The revenue threshold for DWR adoption with crop insurance is identical to the revenue threshold for DWR adoption without crop insurance because the change in expected net insurance payout from adopting DWR is assumed to be $\theta = 0$. The interpretation of the revenue threshold value is if revenue reaches \$882 per acre, we would expect producers to adopt the DWR technology as a way to mitigate the risk associated with climate change.

A change in the expected net insurance payout from adopting DWR to $\theta = 2$ results in values of $\omega_0 = 1.35$ and $\omega_1 = 1.37$. This results in revenue thresholds of \$879 per acre without crop insurance and \$886 with crop insurance. Similarly, a change in the expected net insurance payout from adopting DWR to $\theta = -2$ results in values of $\omega_0 = 1.36$ and $\omega_1 = 1.35$. The ratios result in revenue thresholds of \$881 per acre without crop insurance and \$875 per acre with crop insurance.

Conclusion

As climate change continues to be a growing issue, producers will look for new solutions as a way to deal with climate risk. Issues related to subsidized crop insurance and agricultural conservation technologies are of critical importance, and discussions are occurring regularly. DWR adoption is a potential solution to help producers mitigate the risk of climate change. The resulting theoretical model for DWR adoption provides a foundation for empirically estimating threshold returns for adoption. This provides decision makers monetary estimates on the threshold values of costs and returns required for DWR adoption with and without crop insurance. Only with such an outcome is it possible to assess the likely adoption of any water technology.

The model in this analysis focuses on a specific set of parameter values. The results are preliminary and analysis is limited due to the ongoing data collection process. The assumed parameters will become more concrete as the data collection process is completed. Future analysis will focus on sensitivity analysis of all parameters, particularly the change in expected net insurance payout from adopting DWR. Analysis of the crop insurance parameter will help to reach an improved understanding of the full effect of crop insurance on DWR adoption. Further future analysis will include the influence of alternative government mechanisms including lower crop insurance subsidies and tax credits for pond development to provide decision makers a monetary indication of the degree these mechanisms will influence climate adaptive water use. This model of DWR/crop insurance adoption is universal in its application to a wide variety of investment decisions. As such, it will generate a general discussion on DWR as a method of mitigating the effects of climate change, as well as other practices producers could adopt to manage climate change risk.

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Table 1. Results for the Augmented Dickey-Fuller Unit-Root Test

	Test Statistic	Mackinnon Approximate p-value
Indiana Corn Price Recieved, $/bu	0.8460	0.8868
Indiana West-Central Region Non-Irrigated Yield, bu/acre, 1984-2013	−0.0950	0.6079
Indiana West Central Region Irrigated Yield, bu/acre, 1984-2013	−0.0846	0.6117

Table 2. West-Central Indiana Impounded DWR 80 Acre Field Cost Scenario[a]

	Total Cost	$/acre
Construction (NRCS, 2018)	$177,000	$2,213
Land (PAER, 2018)	58,000	725
Pivot (Kelley, 2018)	49,000	613
Pumping Plant (Dahl, Personal Communication, 2018)	9,000	113
Sunk Cost	**$293,000**	**$3,663**
Land (PAER, 2018)	$214	$3
Electricity (EIA, 2018)	545	7
Labor (NASS, 2013)	2,000	25
Variable Cost	**$2,759**	**$35**

[a] Data sources displayed in parenthesis.

Table 3. Baseline Parameter Values Employed for Producers' Drainage Water Recycling Investment Decisions

Parameter	Description	Value
α_p	Price Drift	0.026
σ_p	Price Volatility	0.241
α_C	Conventional Yield Drift	0.011
σ_C	Conventional Yield Volatility	0.122
ρ_C	Correlation between Price and Conventional Yield	−0.247
α_D	DWR Yield Drift	0.011
σ_D	DWR Yield Volatility	0.120
ρ_D	Correlation between Price and DWR Yield	−0.263
α_{RC}	Conventional Revenue Drift	0.030
σ_{RC}	Conventional Revenue Volatility	0.242
α_{RD}	DWR Revenue Drift	0.029
σ_{RD}	DWR Revenue Volatility	0.239
ρ_R	Correlation coefficient between the uncertainty incorporated in the change of the two revenues	0.990
σ_R	Revenue Volatility	0.001
r	Discount Rate	5%
V	Variable per acre cost of adopting DWR	$34.50
I	Sunk per acre cost of adopting DWR	$3,660
λ_0	Probability crop insurance will not be implemented in the next time interval	0.01
λ_1	Probability crop insurance will be implemented in the next time interval	0.99
Θ	Change in expected net insurance payout from adopting DWR	0

Rc	Per Acre Conventional Revenue	\$649
δ_C	The difference between the expected rate of return and the expected capital gain with no DWR.	0.020
δ_D	The difference between the expected rate of return and the expected capital gain with DWR.	0.021

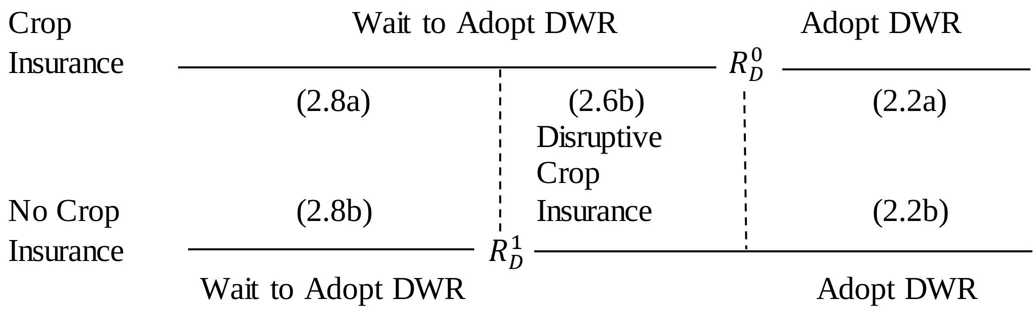

Figure 1. Revenue triggers for adoption of drainage water recycling, DWR

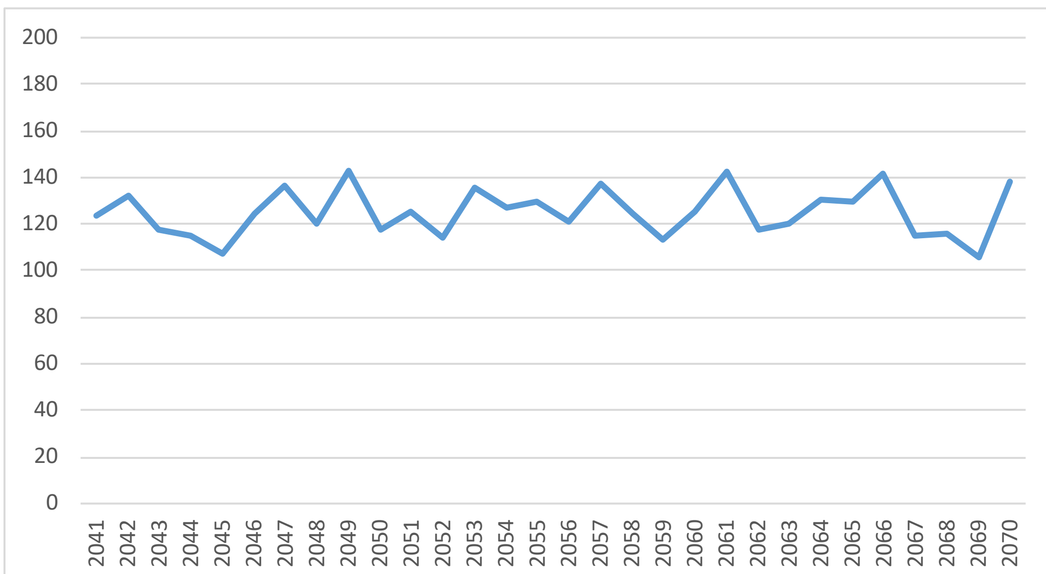

Figure 2. West Central Indiana Non-Irrigated Future Corn Yield, 2041-2070

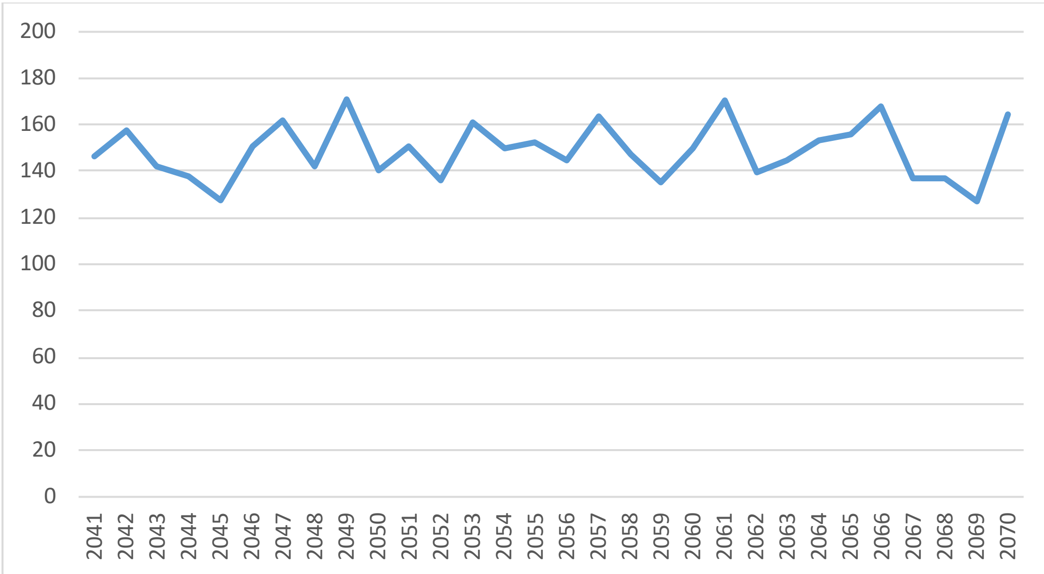

Figure 3. West Central Indiana Irrigated Future Corn Yield, 2041-2070

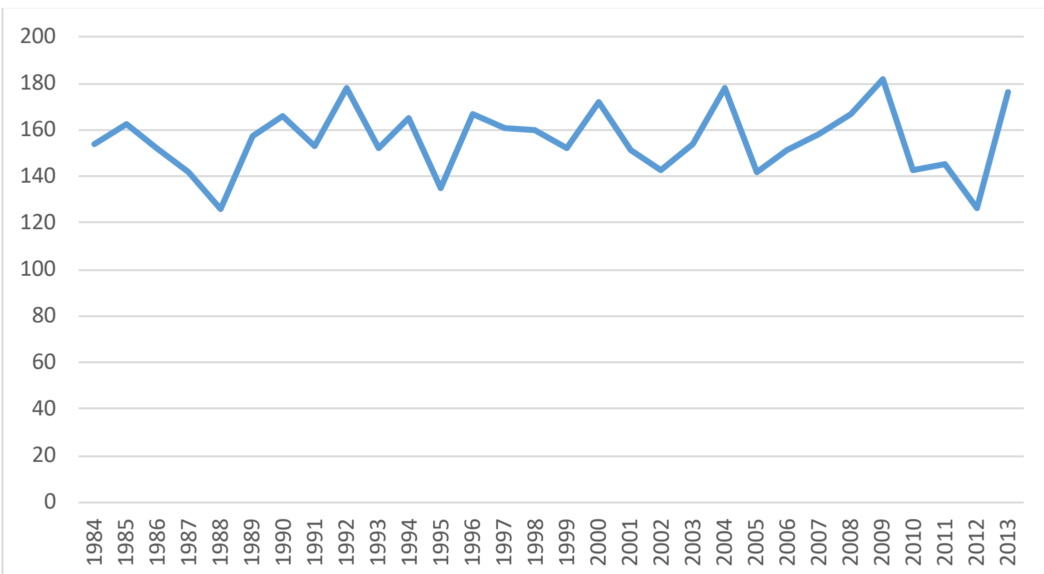

Figure 4. West Central Indiana Non-Irrigated Historic Corn Yield, 1984-2013

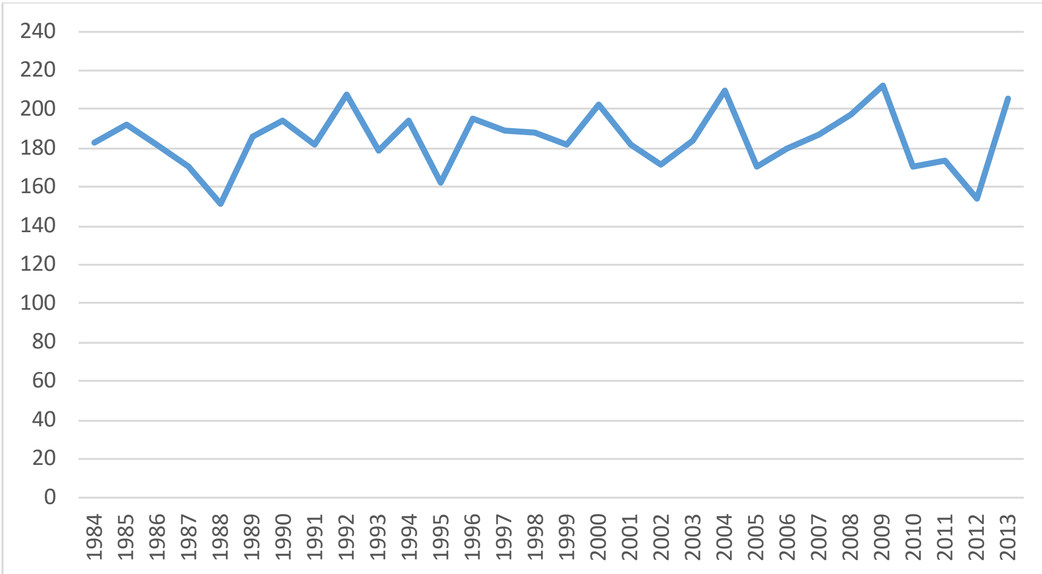

Figure 5. West Central Indiana Irrigated Historic Corn Yield, 1984-2013

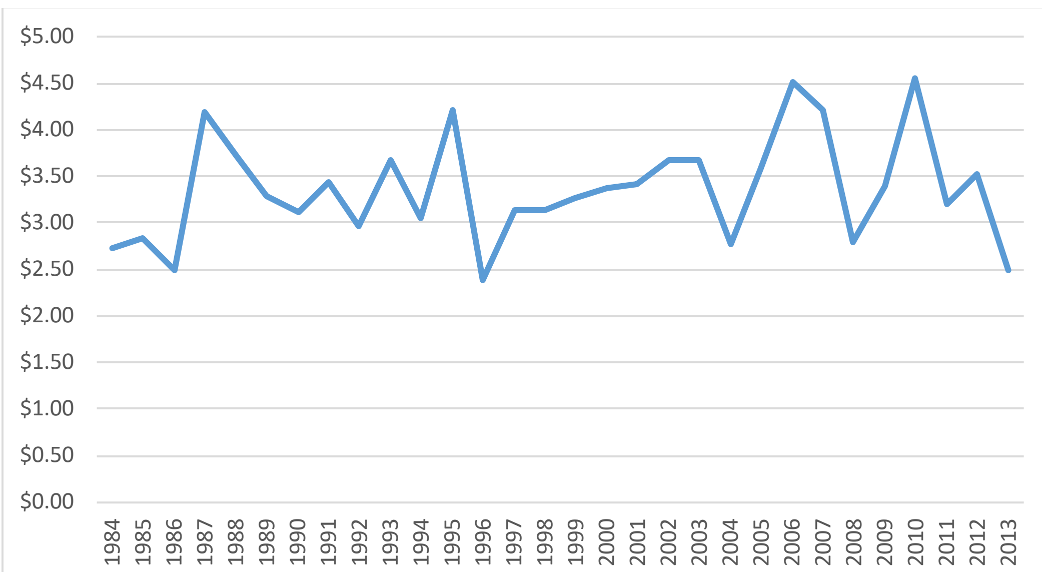

Figure 6. Adjusted Indiana Corn Prices, 1984-2013

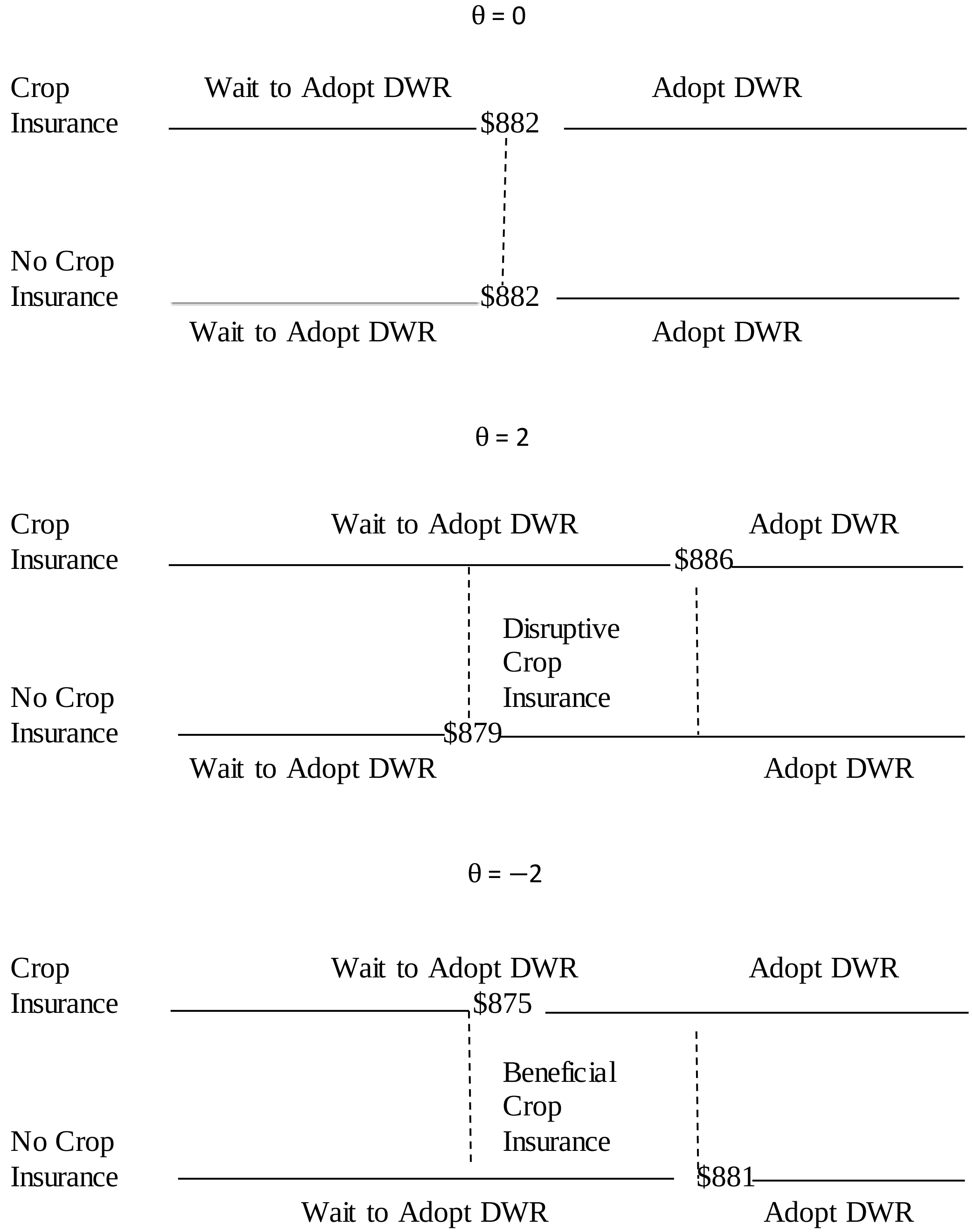

Figure 7. Optimal Revenue Thresholds

Appendix A

$V^0(R_D - R_C) = R_D dt - R_C dt + e^{-rdt} E[V^0[R_D - R_C + d(R_D - R_C)]]$.

Applying Ito's Lemma

$V^0(R_D - R_C) = R_D dt - R_C dt + \frac{1}{1+rdt}[V^0(R_D - R_C) + (\alpha_D R_D V_D^0 + \alpha_C R_C V_C^0)dt +$

$½[V_{DD}^0 \sigma_D^2 R_D^2 + 2V_{CD}^0 \rho \sigma_D \sigma_C R_D R_C + V_{CC}^0 \sigma_C^2 R_C^2]dt$.

Rearranging

$$½[V_{DD}^0 \sigma_D^2 R_D^2 + 2V_{CD}^0 \rho \sigma_D \sigma_C R_D R_C + V_{CC}^0 \sigma_C^2 R_C^2] + (\alpha_D R_D V_D^0 + \alpha_C R_C V_C^0) - rV^0 + R_D - R_C = 0 \qquad \text{(A1)}$$

The particular solution to (A1) is then

$$V^0(R_D - R_C) = \frac{R_D}{r - \alpha_D} - \frac{R_C}{r - \alpha_C}$$

Appendix B

The quadratic equation associated with range (R_D^0, R_D^1) is

$½\sigma^2 \beta(\beta - 1) + (\delta_C - \delta_D)\beta - (\delta_C + \lambda_0) = 0$.

The corresponding characteristic roots, β_1 and β_2, are

$$\beta_1 = \frac{1}{2} - \frac{\delta_C - \delta_D}{\sigma^2} + \sqrt{\left(\frac{\delta_C - \delta_D}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(\delta_C + \lambda_0)}{\sigma^2}} > 1,$$

$$\beta_2 = \frac{1}{2} - \frac{\delta_C - \delta_D}{\sigma^2} - \sqrt{\left(\frac{\delta_C - \delta_D}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(\delta_C + \lambda_0)}{\sigma^2}} < 0.$$

The quadratic equations associated with range $(0, R_D^1)$ are

$½\sigma^2 \beta(\beta - 1) + (\delta_C - \delta_D)\beta - \delta_C = 0$,

$½\sigma^2 \beta(\beta - 1) + (\delta_C - \delta_D)\beta - (\delta_C + \lambda_1 + \lambda_0) = 0$.

The corresponding positive characteristic roots, β_a and β_s, are

$$\beta_1 > \beta_a = \frac{1}{2} - \frac{\delta_C - \delta_D}{\sigma^2} + \sqrt{\left(\frac{\delta_C - \delta_D}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2\delta_C}{\sigma^2}} > 1,$$

$$\beta_s = \frac{1}{2} - \frac{\delta_C - \delta_D}{\sigma^2} + \sqrt{\left(\frac{\delta_C - \delta_D}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(\delta_C + \lambda_1 + \lambda_0)}{\sigma^2}} > \beta_1.$$