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IFPRI Discussion Paper 01016

August 2010

Optimal Rainfall Insurance Contracts for Maize Producers in Ghana's Northern Region

A Mathematical Programming Approach

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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PARTNERS AND CONTRIBUTORS

IFPRI gratefully acknowledges the generous unrestricted funding from Australia, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, the Netherlands, Norway, the Philippines, South Africa, Sweden, Switzerland, the United Kingdom, the United States, and the World Bank.

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ABSTRACT

The risk of food insecurity due to climate change in developing countries has encouraged development partners to seek new approaches to improve the resilience of subsistence agriculture to covariate shocks. Such innovative approaches include investment in safety nets such as rainfall insurance. However, a policy question remains: How does one determine the practicality of rainfall insurance for a particular district? This paper attempts to fill this gap by assessing the viability of rainfall insurance contracts for agricultural production in Ghana's Northern Region. Using a stop-loss framework, an optimal contract is determined by choosing its parameters by maximizing the objective function in the form of covariance between crop loss and indemnity payment, the objective function given a predetermined fair premium rate. The theoretical contract is implemented using monthly rainfall and annual maize crop yield data from 1998 to 2004 from 12 districts in the Northern Region under varying premium rates. We conclude that rainfall insurance may not be viable for all districts in the Northern Region; however, the contracts are likely to be viable in districts that exhibit a positive Pearson correlation coefficient between maize yield loss and indemnity payments.

Keywords: rainfall insurance, climate change, maize yield

JEL Codes: C61, Q18, Q25, Q54

1. INTRODUCTION

Some of the most profound and direct impacts of climate change over the next few decades in Africa will be on agriculture. For example, Kurukulasuriya et al. (2006) predict that revenues from agricultural activities practiced in drylands and livestock sales will suffer the most compared to agriculture practiced in irrigated land from climate change in Africa. Nelson et al. (2009) find that in developing countries, climate change will cause yield declines for the most important crops. By 2050, the decline in calorie availability will increase child malnutrition by 20 percent relative to a world with no climate change. Parry et al. (1999) predict that by 2080, between 55 and 70 million extra Africans will be at risk of hunger due to climate change. Particularly in Africa, climate change is expected to present heightened risk, new combinations of risks, and potentially grave consequences (Ziervogel et al. 2008). The strong dependence on the natural environment for livelihood support combined with a lack of infrastructure and high levels of poverty creates vulnerability in the face of all types of environmental change. Western and central Africa are expected to see agricultural losses ranging from 2 to 4 percent; northern and southern Africa can expect agricultural losses of 0.4 to 1.3 percent by 2100 (Mendelsohn, Dinar, and Dalfelt 2000).

In Ghana, climate change has become a threat to livelihoods. Droughts in parts of the Northern Region have become almost an annual worry to the livelihood of smallholder farmers in particular. The growing climate change risks have alarmed both policymakers and development partners, spurring them to consider contingency plans against possible widespread food insecurity and famine. Although farmers are adopting risk-coping strategies, developing contingency plans is a necessary step since current risk-coping strategies may be ineffective in the face of covariate risks. As Ziervogel et al. (2008) point out, most agricultural systems have a measure of inbuilt adaptation capacity; however, the current rapid rate of climate change will impose new and potentially overwhelming pressures on existing adaptation capacity.

The literature on risk tells us that poor farmers over the years have developed strategies to reduce the impact of both weather and market risks. Kochar (1995) reports that households from villages surveyed by ICRISAT in South India respond to such risks by increasing labor supply. Fafchamps, Udry, and Czukas (1998) show that nonfarm income is positively correlated with shocks affecting agricultural income. In fact, they argue that farmers attempt to work either for wealthier farmers or in nonagricultural sectors such as brick making, carpentry, collecting firewood, or informal shopkeeping when the once reliable agricultural sector fails to help them meet their livelihood needs. However, nonagricultural-income-generating activities are not always available as they require capital and education levels that poor farmers, in most cases, lack. In addition, risk-coping strategies have proven ineffective given the gravity and covariate nature of climate change risks (Skees, Hazell, and Miranda 1999). For example, after a shock farmers tend to sell their livestock to smooth consumption. But since every farmer in the region will also sell his or her livestock, livestock prices will plummet along with expected revenue. Further, according to the World Food Programme (2005, 7):

> *Because of the extreme and covariant nature of the risks they face, and in the absence of risk-management instruments such as crop insurance, risk-averse smallholder farmers naturally seek to minimize their exposure . . . by opting for lower-value (lower-risk) and therefore lower-return crops, using little or no fertilizer and overdiversifying their income sources. These risk-management choices also keep farmers from taking advantage of profitable opportunities; they are a fundamental cause of continued poverty.*

Therefore, public intervention is justified on the basis that the covariate risks farmers face may lead to a poverty trap. Some such public interventions include investment in irrigation, drought early warning, and rainfall insurance. Irrigation or small-scale water harvesting units are practical means to reduce the impact of climate change on the prevalence of food insecurity in Africa (Ngigi 2009). In addition to lowering crop vulnerability to precipitation shocks, access to irrigation encourages farmers to invest in new technology such as high-yield varieties that in most cases require more water and care than the traditional seed varieties. Access to irrigation will also increase farm return.

Investing in drought-early-warning infrastructure can also be useful to communities threatened by increased weather variability. Such infrastructure enables farmers to tailor farm management decisions in the season ahead. Although such technology is not yet widely spread in Africa, researchers have found considerable demand for it in various countries. For example, using contingent valuation methods, Makaudze (2005) identified a substantial welfare benefit in a wide-scale, improved seasonal forecast system among Zimbabwean farmers. In Tanzania, studies were done to identify the trends of onset dates, cessation dates, and variability of rainfall seasons particularly during El Niño/La Niña years (Mhita, Tibaijuka, and Tillya 2003). According to those authors, outcomes are important for agricultural planning because El Niño–Southern Oscillation accounts for about 50 to 60 percent of precipitation variability. The results can also be used to establish weather-forecasting infrastructure to warn farmers against potential dry spells.

Finally, interest has increased in introducing weather-based crop insurance contracts as a means to help farmers break out of the vicious cycle of poverty (Barnett, Barrett, and Skees 2008). Such contracts can be sold at the farm, district, or country level to help speed up the relief effort after a covariate shock (Chantarat et al. 2007). Sarris, Karfakis, and Christiaensen (2006) estimate the demand for rainfall-based crop insurance among villages located in the base of Mt. Kilimanjaro in terms of willingness to pay. They found evidence of a welfare benefit of such crop insurance. Similar results were found when estimating the welfare benefit of a remote-sensed-vegetation-based crop insurance among Zimbabwean farmers (Makaudze 2005).

Although irrigation and drought-early-warning infrastructure can be an ideal policy recommendation, the initial investment for such infrastructure may prove too expensive for rural communities to afford. On the other hand, index-based rainfall insurance is relatively inexpensive; its minimum requirements include adequate training for both farmers and local monitoring agents. Further, unlike the traditional insurance contract, the monitoring cost of rainfall insurance is negligible (Skees, Hazell, and Miranda 1999). But rainfall insurance may not be viable everywhere. Certain conditions must be in place to guarantee its sustainability.

The purpose of this paper is to design an optimal rainfall insurance contract and assess its viability in insuring rainfall risks at an actuarially fair premium rate and adequate probability of indemnity using the case of maize producers in districts of Ghana's Northern Region. Specifically, this paper addresses the following questions: What is the optimal contract design for each district? How efficient is rainfall-based insurance in covering losses? How does the risk reduction effectiveness of rainfall-based insurance vary across districts?

Section 2 introduces the index-based insurance contract. Section 3 reviews the literature on index-based insurance. Section 4 introduces a theoretical framework for designing such insurance. In Section 5 we present a numerical application for the case of maize producers in the Northern Region of Ghana, and Section 6 concludes with policy recommendations.

2. INDEX-BASED INSURANCE

Index-based insurance (or index insurance) is a contract that pays for losses based on an index, an independent and objective measure that is highly correlated with losses such as extreme weather. Index-based insurance contracts, such as rainfall insurance, circumvent the moral hazard and adverse selection problems that plague traditional insurance (Skees 2008). Moral hazard is suppressed since farmers' indemnification is independent of their individual losses. On the other hand, adverse selection is suppressed because every farmer faces the same insured risks.

Regardless of how an insurer is able to pool its risks, it must also be insured by a reinsurance entity. As Miranda and Glauber (1997) point out, index-based insurance must be reinsured by a reinsurer to ensure its survival; they argue that without affordable reinsurance, index-based insurance is doomed to fail. Some reinsurance options include traditional reinsurance, catastrophe bonds, and the recently introduced World Bank reinsurance vehicle, the Global Index Insurance Facility (World Bank 2005).

Multiple conditions, including the following (Skees 2008), need to be met for the design and successful implementation of an index insurance contract:

- Weather event must create correlated losses.
- Index must be a good proxy for loss.
- Event must be observable and easily measured.
- Third party should be involved in the measurement.
- System must be objective and transparent.
- Historic data must exist to price the risk.

Assuming the existence of a demand for insurance and a substantial level of risk aversion, the index insurance is sold at an actuarially fair premium by standard units—meaning the agency will sell vouchers that entitle the insured to a predetermined payment depending on rainfall volume. The voucher is similar to a lottery ticket or coupon that the insured redeems to receive his or her seasonal indemnity payment at a predetermined due date.

The insurance program has *threshold* and *limit* rainfall volume levels between which the process of indemnification will be executed. The threshold is the accumulated rainfall volume that will trigger the payment of indemnity, and the limit is the minimum level that will set maximum liability payment. Once the threshold is reached, the indemnity payment will start and will incrementally increase until the index reaches the limit.

The following example (USAID 2006) illustrates the structure of an index insurance contract for rainfall risk that begins making payments when seasonal rainfall is 100 millimeters or less. The maximum indemnity payment is made when rainfall is at or below 50 millimeters for the season. Assuming that the policyholder pays for $50,000 in liability, the index insurance contract will be characterized as follows:

- Index variable: total accumulated rainfall measured at a local weather station for the cropping season
- Threshold: 100 millimeters of rainfall
- Limit: 50 millimeters of rainfall
- Liability purchased by the policyholder: $50,000
- Payment rate:
  = (threshold – actual value)/(threshold – limit)
  = (100 – actual value)/(100 – 50)
- Indemnity payment**:** The payment rate multiplied by the total liability:
  = (100 – actual)/(100 – 50) × $50,000

Table 1. Payments due under different rainfall level scenarios

Total Rainfall (millimeters)	Indemnity Payment Due
110	None. The threshold has not been reached.
80	(100 – 80)/(100 – 50) × 50,000 = $20,000
50	(100 – 50)/(100 – 50) × 50,000 = $50,000
40	$50,000. 50-millimeter limit has been exceeded.

Source: USAID (2006).

3. LITERATURE REVIEW

The most quoted theoretical work on index insurance is Miranda (1991), who outlines both theoretically and empirically how efficiently, relative to a traditional insurance contract, the index insurance contract covers farmers' risks. The paper theoretically shows that the farmer whose sensitivity to the chosen index is the highest will benefit the most from the index insurance contract. Using panel data from Kentucky soybean farmers from 1974 to 1988, under various scenarios, Miranda estimates and compares the risk reduction impact of traditional insurance with that of index insurance with a full coverage level and an optimum coverage level. He finds that traditional insurance reduces on average 30.8 percent of risk, index insurance with full coverage reduces on average 22.4 percent of risk, and index insurance with optimum coverage reduces on average 39.1 percent of risk. Thus, index insurance has the potential to reduce more risk than the traditional insurance contract.

Mahul (1999) presents a theoretical framework for designing a stop-loss index insurance contract by choosing optimal stop and loss points that maximize the covariance between an indemnity function and a loss function subject to a premium function. In lower-income countries, weather insurance has been proposed as a tool to improve drought response for famine prevention (Chantarat et al. 2007, 2008), to enhance microfinance institutions (Miranda and Gonzalez-Vega 2010; Skees and Barnett 2006), and to insure against flood (Khalil et al. 2007).

Molini et al. (2007) specify an indemnification schedule for index-based crop insurance with the goal of preventing rural income from dropping below the poverty line in northern Ghana. They used nonparametric methods to estimate the optimal indemnification schedule that minimizes farmers' risk of falling below the poverty line. Unlike the present paper, Molini et al. used farmer-level data from four rounds of the Ghana Living Standard Survey, 1987/88, 1988/89, 1991/92, and 1998/99, plus time series data for monthly rainfall at 40 stations throughout Ghana. Their goal was to propose a vehicle for public–private safety nets in which poor farmers are offered a subsidized contract that supplements their income in case of price and/or weather shocks.

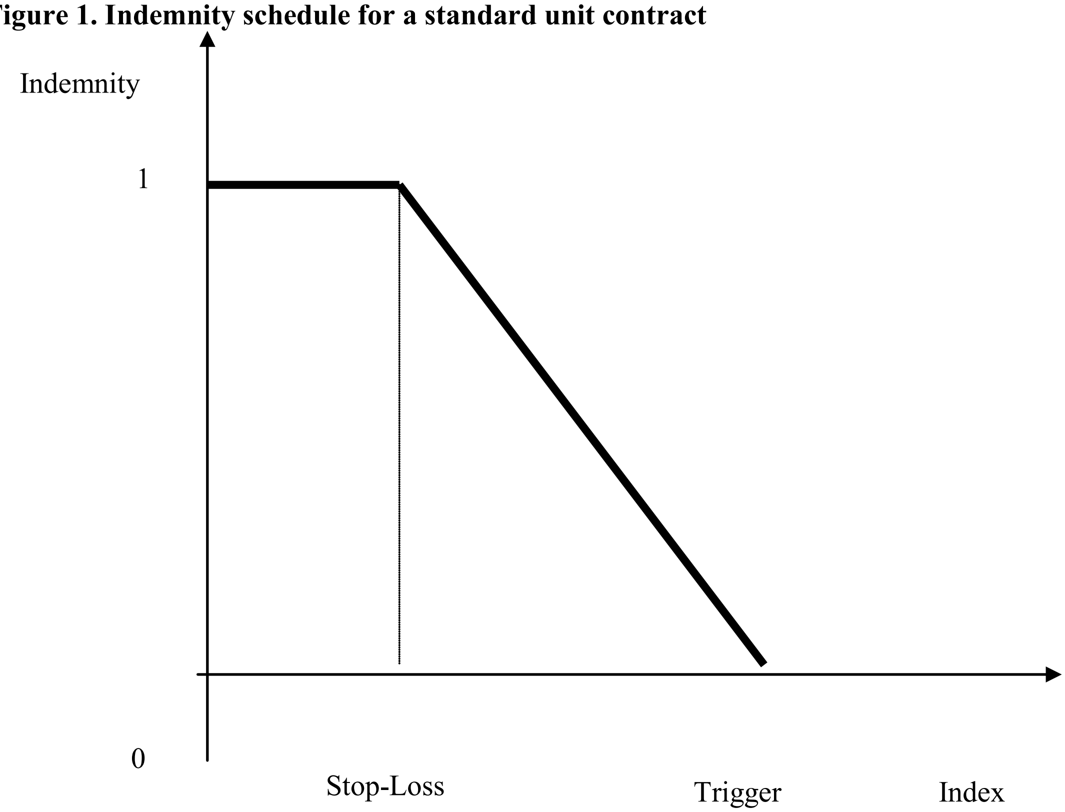
In terms of implementation, a growing number of pilot programs are being implemented in places such as Peru, Mongolia, Morocco, and very recently Malawi and Kenya. Because of a lack of reliable time series data on rainfall levels, the Peruvian program used the El Niño–Southern Oscillation as a regional proxy for rainfall levels. Plus, the insurance contracts can be purchased by banks or microfinance institutions to insure their agriculture-related loan portfolios against the risk of financial losses associated with catastrophic weather events. The Mongolian program uses regional livestock mortality rates as an indicator for indemnifying livestock farmers against their loss. In Malawi, a pilot project offered a packaged loan and index-based microinsurance product to groups of groundnut farmers organized by the National Smallholder Farmers Association (Hess and Syroka 2005); farmers collect an insurance payment if the index reaches a certain measure, or "trigger," regardless of actual losses. Recently, the International Livestock Research Institute (ILRI) in collaboration with other institutions launched a livestock insurance program for the subsistent pastoral population in northern Kenya. They use satellite imagery of forage as an index for the shortage of forage, which correlates with high cattle mortality. When the predicted mortality rate crosses a predetermined threshold, the insurance program will indemnify the cattle herders.

The present paper uses a simple, straightforward approach to assessing the practicality of an index insurance contract prior to its implementation in a particular region or locality. We use a mathematical programming approach that seeks the insurance contract that optimally maximizes the covariance between the indemnity function and the loss function. The procedure we use will allow policy analysts to identify the practicality of a possible rainfall index insurance program by identifying its parameters and testing its ability to track rainfall shocks. Further, this paper uses both nonparametric and numerical approximation methods to both identify the distribution of the rainfall index and test its ability to track rainfall shocks.

4. DESIGNING AN INSURANCE CONTRACT

The purpose of this section is to provide a conceptual framework for designing a rainfall insurance contract. Let $g(x)$ denote indemnity paid per dollar of liability conditional on realization of the prescribed index x, a nonnegative random variable with a differentiable cumulative distribution *F*. As shown in Figure 1, the contract pays nothing if the index x exceeds the predefined "trigger" τ and pays full indemnity if the index falls below the predefined "stop-loss" *u* (assuming a maximum indemnity of 1). The contract pays a proportional indemnity $\frac{(x\text{-}\mu)}{(\tau\text{-}\mu)}$ whenever the index lies between the trigger *τ* and the stop-loss *u*.

Figure 1. Indemnity schedule for a standard unit contract



Source: USAID (2006).

The loss-contingent indemnity of this contract is expressed as

$$g(x; L, \tau, \mu) = L.\min(\max(\frac{\tau - x}{\tau - \mu}), 0), 1), \quad \tau > \mu \tag{1}$$

where *L* denotes the liability, which is normalized here to 1. The contracts are purchased by district-level authorities within the same region. Our methodology for selecting the optimum rainfall insurance contract is based on the approach developed by Vedenov and Miranda (2001). In particular, we search for values for the trigger and stop-loss so as to maximize the covariance between losses of interest and indemnities, while not allowing the expected loss cost, also known as the "fair premium rate," to exceed a prescribed level of affordability, here assumed to be 5 percent, 10 percent, and 15 percent of liability. The fair premium rate is obtained by estimating the expected indemnity divided by the liability. See the appendix, where we derive the fair premium rate as

$$\pi = \frac{1}{\tau - \mu} \int_{\mu}^{\tau} (1 - F(x))dx \quad . \tag{2}$$

Therefore, considering a rainfall index insurance that indemnifies district when its random yield y_i falls below percent θ of the average rainfall $\theta\overline{y}$, the optimum contract is the optimal solution to the following optimization problem:

$$\begin{aligned} &\underset{\tau,\mu}{Max}\, Cov\{g(x; L, \tau, \mu),\ \max(0,\ \theta\overline{y} - y_i)\} \\ &s.t.\ \pi = \frac{1}{\tau - \mu} \int_{\mu}^{\tau} (1 - F(x))dx \end{aligned} \quad , \tag{3}$$

where $\max(0, \theta\overline{y} - y_i)$ is the district loss schedule. We use annual corn yield data from 1998 to 2004 from 12 districts in the Northern Region of Ghana. We first compute the individual district correlation coefficient between rainfall and crop yield to estimate the sensitivity of maize yield to rainfall. Then, we solve the maximization problem shown in Equation 3 to estimate the optimum contract considering three different premium rates. Finally, we verify the ability of the proposed contract to insure against loss by retracing its performance had it been administered in the years during which the data were collected.

5. NUMERICAL APPROXIMATIONS

The data used to design and assess the insurance contracts are from two sources. The rainfall data were collected from the Famine Early Warning System satellite database published by the National Oceanic and Atmospheric Administration (NOAA). NOAA set up a website that allows users to acquire rainfall data from 1998 to 2005 from anywhere in Africa just by using geographical coordinates.[1] Maize yield data were collected by the Ghanaian Ministry of Food and Agriculture between 1992 and 2007 (Ministry of Food and Agriculture 2007). The dataset includes crop yields for 12 districts of the Northern Region of Ghana. However, due to the data limitation, the present study uses only the rainfall and crop yield data from 1998 to 2004. Ideally we would prefer a much longer time series to capture seasonal trends and ensure both the consistency and the efficiency of estimated parameters.

Table 2 presents the correlation coefficients (CCs) between monthly rainfall and annual maize yield for each district. Our results suggest that the CC between maize yield and rainfall varies widely across districts and over time. In fact, maize yield is most correlated with rainfall during the months of July and August with an average CC of 0.41 and 0.35, respectively. Some of the CCs appear to be negative. This implies that rainfall for these particular months is not a suitable index for maize yield loss due to drought. The present paper instead uses annual rainfall as the index. In Figure 2, we compute the CC between total annual rainfall and annual maize yield. We find that only three out of 12 districts have CCs less than zero; the low-CC districts are East Dagomba, West Mamprusi, and West Gonja. This implies that annual rainfall volume is not a good index of maize yield loss for those districts.

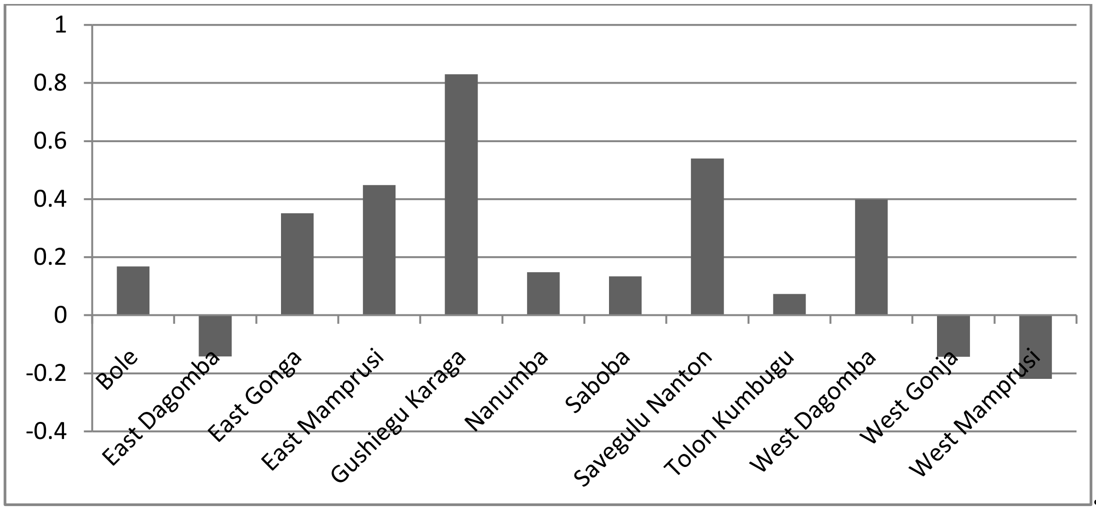
Table 2. Correlation coefficients between maize yield and monthly rainfall by district and month

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Bole	0.02	0.03	-0.05	0.48	0.34	-0.16	0.41	0.12	-0.29	-0.59	0.07	0.30
East Dagomba	0.34	-0.64	0.23	0.09	0.29	-0.27	0.14	0.14	-0.83***	0.40	0.23	0.42
East Gonga	0.28	0.66	-0.51	-0.58	-0.77***	0.43	0.91***	0.54	0.49	-0.28	0.53	-0.32
East Mamprusi	0.84***	0.29	0.25	0.62	-0.27	0.21	0.75*	0.03	-0.13	-0.21	0.59	-0.14
Gushiegu Karaga	0.53	0.58	0.34	0.06	-0.74*	0.78***	0.87***	0.79***	0.46	-0.16	0.54	0.22
Nanumba	0.09	0.71*	-0.48	-0.75*	-0.81***	0.06	0.25	0.49	0.54	-0.16	0.45	0.33
Saboba	0.36	0.19	0.39	0.27	-0.47	0.13	0.72*	0.41	0.11	0.26	0.49	-0.26
Savegulu Nanton	-0.17	0.95**	-0.22	0.05	-0.4	0.60	-0.08	0.33	0.18	-0.23	-0.01	-0.37
Tolon Kumbugu	-0.15	0.50	0.16	0.36	-0.41	0.14	0.27	0.59	0.00	0.1	0.36	-0.44
West Dagomba	0.30	-0.70*	0.28	-0.57	-0.47	-0.48	0.41	0.37	-0.18	0.38	0.22	0.66
West Gonja	0.14	-0.23	-0.42	-0.42	0.08	-0.05	-0.02	-0.08	0.08	-0.27	-0.46	0.48
West Mamprusi	0.46	0.39	-0.69*	-0.61	-0.20	0.07	0.23	0.45	0.57	-0.38	0.45	0.52
Average	0.25	0.23	-0.06	-0.08	-0.32	0.12	0.41	0.35	0.08	-0.10	0.29	0.12

Source: Authors' calculations.
Note: * significant at 10%. ** significant at 5%. *** significant at 1%.

[1] http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.CPC/.FEWS/.Africa/.

Figure 2. Correlation coefficient between annual rainfall and maize yield



Source: Authors' calculations.

To design the insurance contract, we calculate average long-run rainfall volume for each district, and if a district incurs rainfall 15 percent below the long-run average, it is indemnified based on the illustration presented in figure (1). The choice of 15 percent was not made deliberately but rather was made based on the norm in the literature (Miranda 1991).

Next, we estimate the probability density function of the index for each district. Given the limited dataset, we used kernel density estimation. Kernel density estimation is implemented through the ks density function in MATLAB®. This function provides automatic data-driven bandwidth that is optimal for estimating normal densities. On average, the index follows a normal distribution with a single trough except for a few districts where we observe nonnormal distributions (see Figure 3). A well-behaved index distribution, a normally distributed index, is ideal for designing an insurance contract as it implies that the contract will most likely pay a proportional indemnity of $\frac{(x-\mu)}{(\tau-\mu)}$. Not all districts have a well-behaved index distribution. This might be caused by a limited sample size. Indeed, as sample size increases, distributions tend to converge toward normal distribution.

After estimating the distribution of the index for each district, we solve for the optimal contract by solving the optimization problem (Equation 3). This is done assuming a 5 percent premium, 10 percent premium, and 15 percent premium, respectively, using simple numerical approximation techniques. We first compute the loss function for each district, and we then generate a trigger grid using the annual rainfall volume as the maximum trigger point. Next, we compute the covariance between the loss function and the indemnity function maximizing triggers and stops for each region and for targeted premium rates. Last, we use the trapezoidal rule[2] to compute the stop that yields the target rate for a given trigger and target rate, and we employ a simple grid search over triggers to find the optimum.

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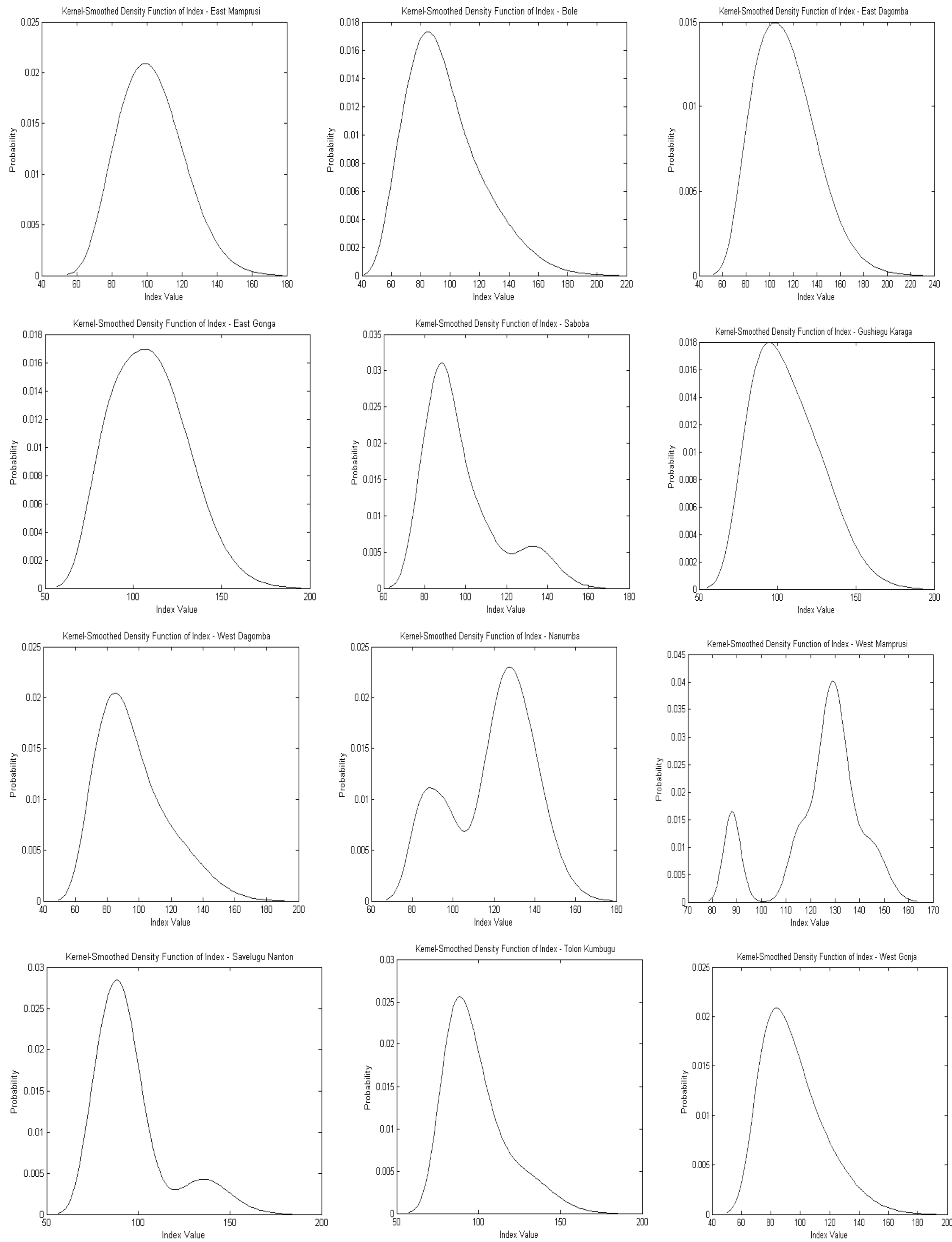
[2] The trapezoidal rule is an approximate technique for calculating the definite integral $\int_a^b f(x)dx$ such that $\int_a^b f(x)dx \approx \frac{(b-a)\left(f(a)+f(b)\right)}{2}$.

Figure 3. Kernel-smoothed density function of district index



Source: Authors' calculations.

Table 3. Insurance contracts

District	Premium rate = 5%			Premium rate = 10%			Premium rate = 15%		
	Stop	Trigger	loss Indem Corr	Stop	Trigger	loss Indem Corr	Stop	Trigger	loss Indem Corr
Bole	0.05	82.83	0.07	21.08	89.6	0.08	0.02	105	0.15
East Dagomba	55.9	88.09	-0.16	75.1	87.63	-0.16	83.61	89.04	-0.16
East Gonga	62.27	85.82	0.36	77.06	85.8	0.36	85.67	85.83	0.36
East Mamprusi	64.9	81.51	1.00***	77.32	81.51	1.00***	83.21	83.21	1.00***
Gushiegu Karaga	0.06	97.39	0.73*	23.96	104.4	0.77***	50.77	104.4	0.77***
Nanumba	73.28	89.5	-0.17	84.84	89.57	-0.17	0.01	138.5	-0.08
Saboba	71.37	78.51	1.00***	78.51	78.52	1.00***	80.89	80.91	1.00***
Savegulu Nanton	0.03	90.08	0.37	5.28	98.4	0.39	36.32	98.4	0.39
Tolon Kumbugu	0.05	92.79	0.15	0.04	102.7	0.38	2.43	110.99	0.41
West Dagomba	59.18	71.91	-0.22	69.66	71.95	-0.22	74.21	74.21	-0.22
West Gonja	48.8	76.7	-0.09	63.92	76.7	-0.09	71.31	76.73	-0.09
West Mamprusi	82.94	90.16	-0.17	0.01	135.9	-0.1	0.02	145.4	-0.06

Source: Authors' calculations.
Note:* significant at 10%. ** significant at 5%. *** significant at 1%.

After estimating the maximum covariance, we calculate the Pearson correlation coefficient by dividing the covariance by the product of the standard deviations of the loss and indemnity function. Table 3 presents the stop points, the trigger points, and the Pearson correlation coefficient (loss Indem Corr) between crop loss and indemnity for each district at the 5 percent, 10 percent, and 15 percent premium rates. Both the magnitude and the sign of the CC between crop loss and indemnity determine whether rainfall insurance will be viable in a given district. Ideally, a positive CC close enough to 1 should be attractive to both the farmer and the insurance company. A negative CC implies that loss and indemnity payment are negatively related, suggesting that farmers will not be indemnified when they incur a loss or they will be indemnified when they do not incur a loss. Rainfall, therefore, is not a good indicator of loss in that particular district. Further, a unitary CC implies that the loss of maize yield in that district is highly correlated with indemnity payment, which corresponds to the ideal scenario. Based on the above criteria, only seven districts (Bole, East Mamprusi, East Gonga, Gushiegu Karaga, Saboba, Savegulu Nanton, and Tolon Kumbugu) may afford viable rainfall-based index insurance because of the positive CC. However, due to the low degrees of freedom only three districts, East Mamprusi, Gushiegu Karaga, and Saboba, have a significant CC at the 10 percent confidence interval.

Lastly, we test how the proposed insurance contract would have performed had it been available to those districts. This involves retracing the performance of each insurance contract discussed in Table 3 had it been administered between 1998 and 2004. For each year, we estimate the loss that each district incurred (represented in Figure 4 by the thick line). The indemnity payments for the 5 percent, 10 percent, and 15 percent premium rates are represented by the solid line, dashed line, and dotted line, respectively. The insurance contract that captures most losses is the one that allows the indemnity payments to cover most of the losses.

From the results in Figure 4, districts with a negative CC between loss and indemnity benefit the least from the rainfall insurance. The districts that do benefit from the insurance contract are those with a positive CC between loss and indemnity. The two districts with a unitary CC do not seem to profit from the insurance at first glance. But it is hard to tell because the two districts incurred a loss only once out of the seven years observed. Since the loss was rather small, they could not have been indemnified. Had the loss been significant in magnitude or had it incurred in multiple years, the insurance would have covered most of it.

Figure 4. Indemnity versus losses assessments

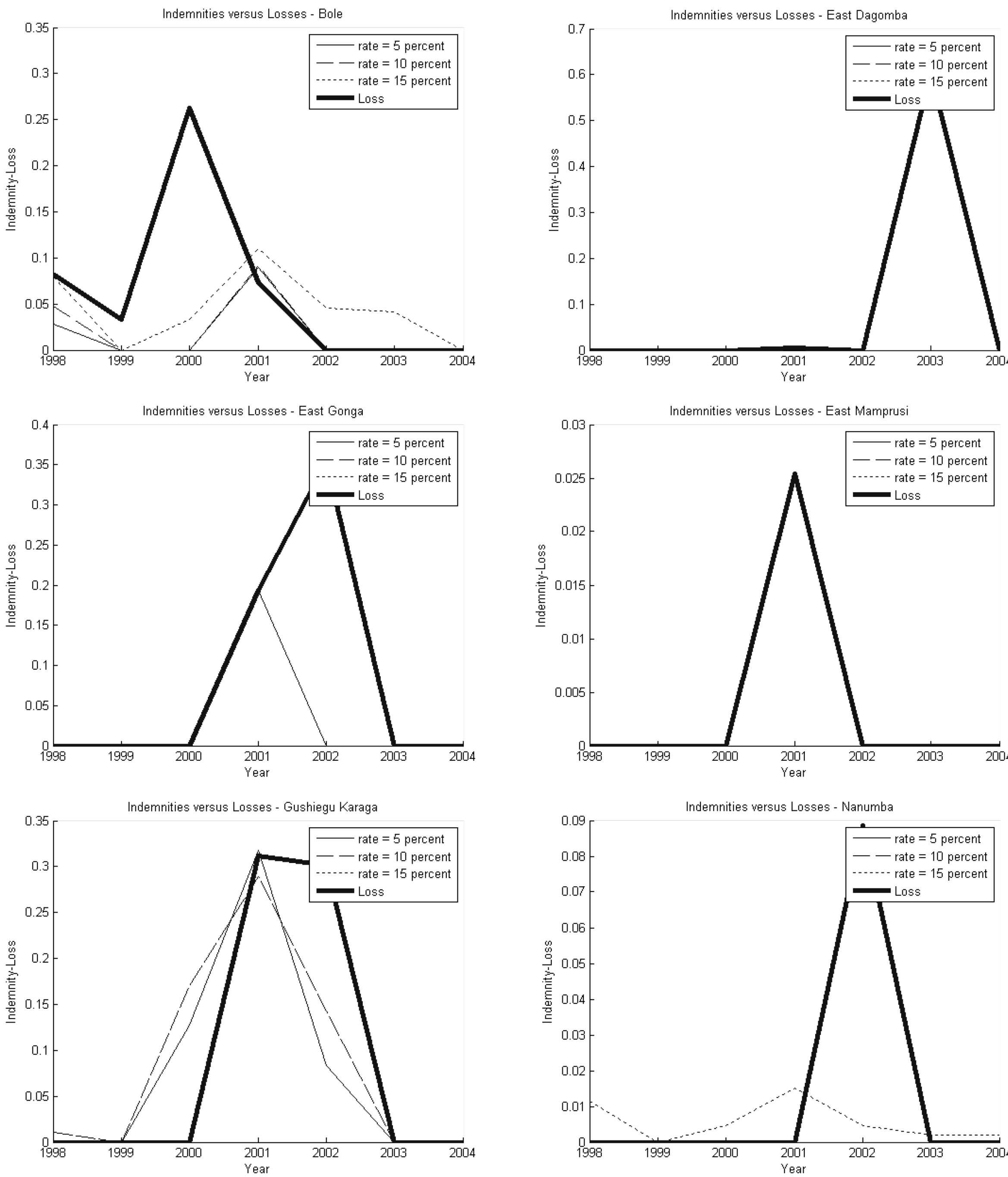
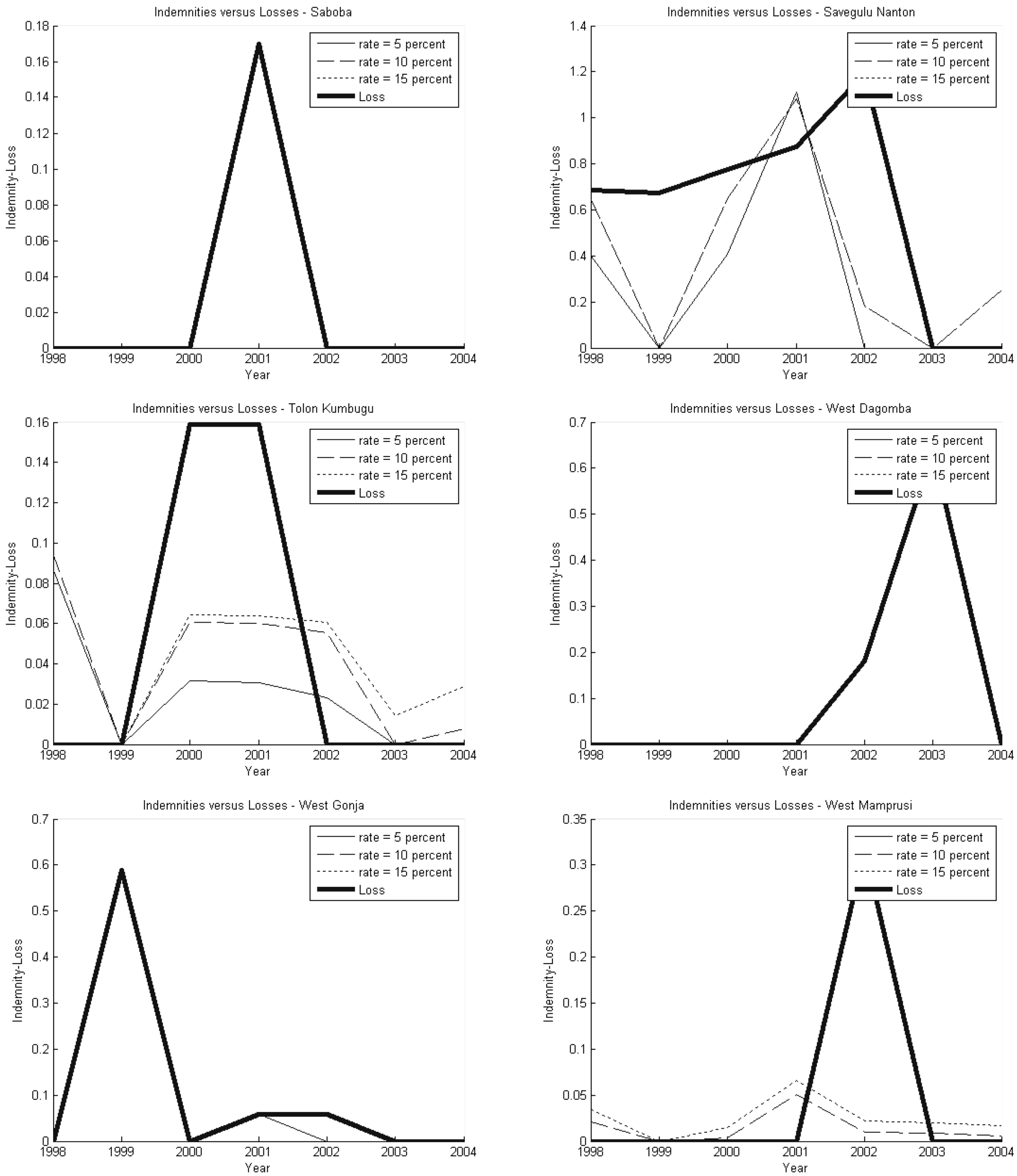


Figure 4. Continued



Source: Authors' Calculations.

Specifically, the districts that benefit the most from the insurance contract are Gushiegu Karaga and Savegulu Nanton, which appear to have a higher CC between loss and indemnity. On the other hand, the districts of East Dagomba, Nanumba, West Dagomba, West Gonja, and West Mamprusi benefit the least from the insurance contract, as they have a negative CC between loss and indemnity.

6. CONCLUSION

In the present paper we design and assess rainfall insurance contracts for maize production in districts in Ghana's Northern Region. This study was motivated by the growing threat climate change poses in the region coupled with the desire of local policymakers to put in place policy recommendations to address the risks of climate change. The paper does not price the proposed insurance contract. That will require field studies to determinate the willingness to pay for the proposed insurance in addition to financial engineering procedures that are beyond the scope of this paper. Chantarat et al. (2008) and Molini et al. (2007) present good illustrations of pricing index insurance in a developing-country setting. The present paper presents an ex ante policy assessment for testing the practicability of rainfall insurance. This is done simply by establishing the optimal trigger and loss points that maximize the Pearson correlation coefficient between a crop loss function and an indemnity payment function.

Our findings suggest that rainfall insurance might not work for all districts. Some districts displayed a negative CC between crop loss and indemnity payment. In such cases, the insurance contract is not attractive for either the insured or insurer. Therefore, rainfall may not be an ideal index for loss at least for those districts displaying a negative CC between maize loss and indemnity. Perhaps indexes such as area yield (Miranda 1991) or remote-sensed vegetation (Makaudze 2005) would perform better in the design of optimal crop insurance.

Policymakers should consider rainfall insurance as a possible instrument for protecting farmers against climate change risks. Its relatively inexpensive operation and monitoring costs make it attractive. On the other hand, proper ex ante assessment, as proposed in this paper, ought to be done to identify the ideal index and to establish whether a location will benefit from it. We must stress that our results were limited by the relatively short time period used for the analysis, which reduced the degrees of freedom to six. In practice, designing a rainfall insurance contract requires longer historical rainfall and crop yield observations to capture structural relationships between the two variables and design a more accurate contract. If long run rainfall data are not available, they can be substituted with El Niño–Southern Oscillation indices, which are available as far back as the 1800's, assuming that they are correlated with crop loss in the location of interest.

APPENDIX: FAIR PREMIUM RATE DERIVATION

Assuming indemnity to be $g(x;L,\tau,\mu) = L.\min(\max(\frac{\tau - x}{\tau - \mu}),0),1)$, fair premium rate is derived by taking the expected value of indemnity and dividing it by liability *L*. Formally:

$$\pi = Eg(x;L,\tau,\mu) = \int I(x_t)f(x_t)dx_t$$

$$= \int_{-\infty}^{\mu} I(x_t)f(x_t)dx_t + \int_{\mu}^{\tau} I(x_t)f(x_t)dx_t + \int_{\tau}^{\infty} I(x_t)f(x_t)dx_t$$

$$= \int_{-\infty}^{\mu} f(x_t)dx_t + \int_{\mu}^{\tau} \frac{\tau - x_t}{\tau - \mu} f(x_t)dx_t + 0$$

$$= F(\mu) + \frac{1}{\tau - \mu}[\tau \int_{\mu}^{\tau} f(x_t)dx_t - \int_{\mu}^{\tau} x_t f(x_t)dx_t]$$

$$= F(\mu) + \frac{1}{\tau - \mu}[\tau F(\tau) - \tau F(\mu) - \int_{\mu}^{\tau} x_t dF(x_t)]$$

$$= F(\mu) + \frac{1}{\tau - \mu}[\tau F(\tau) - \tau F(\mu) - x_t F(x_t)\Big|_{\mu}^{\tau} + \int_{\mu}^{\tau} F(x_t)dx_t]$$

$$= \frac{1}{\tau - \mu}\int_{\mu}^{\tau} F(x_t)dx_t$$

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