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Index Insurance: Using Public Data to Benefit Small-Scale Agriculture

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Abstract

This paper highlights the importance of public data for the development of more efficient and sustainable risk management schemes, such as index insurance, for smallholder agriculture. Three case studies of index insurance—catastrophic weather insurance in Mexico, satellite-based insurance for pastoralists in Kenya, and a hypothetical area-yield insurance scheme in Ecuador—are briefly analyzed in terms of the data and type of index used, the way the contract was designed and implemented (or simulated) and the impacts of the insurance on investment, nutrition and income smoothing. The increasing opportunity to use *big data* for improving and expanding index insurance is also addressed. The analysis suggests that the strong potential for index insurance to improve the welfare of small farmers represents a clear justification for increased government investment in the collection of the types of data that can facilitate the expansion of index insurance markets.

Keywords: Index insurance, public data, big data, small farmers, developing countries

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Introduction

Many governments in developing countries have, in the new millennium, prioritized the creation and strengthening of the agricultural crop insurance markets. Multiple motivations underlie these insurance initiatives. First, governments are concerned about the pressure placed on public budgets by the increasing frequency of catastrophic weather events, such as severe droughts, flooding and frost, associated with climate change. Strengthening formal insurance is seen as a more efficient means of managing this risk than ex-post disaster relief. Second, addressing missing or incomplete insurance markets is increasingly viewed as a necessary step to enhance food security and reduce poverty. Without insurance, farm households, especially small-holders who continue to account for the majority of basic grain production in many developing countries, are often unable to make investments because banks refuse to offer credit to uninsured farmers. Those who do have access to credit are often unwilling to seek credit because the collateral requirements would expose them to too much risk (Boucher et al. 2008). The end result of under-developed insurance markets is a vicious cycle of under-investment, stagnant agricultural yields and the persistence of rural poverty.

While the logic of strengthening agricultural insurance markets is clear, the path forward is much less so. One option is to build a market for conventional named peril (or indemnity) insurance. The challenges of creating a broad and sustainable market for conventional insurance contracts in developing country settings, however, are considerable. The combination of information asymmetries and poor infrastructure present the largest hurdle. Conventional contracts require multiple field inspections in order to evaluate losses and determine if they were caused by insurable events instead of farmer negligence (moral hazard). When telecommunications and road infrastructure are poor, the costs of effectively carrying out these types of inspections and overcoming information asymmetries between the farmer and the insurance company can be prohibitively high, thus undermining the viability of the insurance market, unless that it benefits from massive subsidies.[1]

Index insurance represents an attractive alternative, especially in small farmer contexts.[2] Under an index insurance contract, indemnity payments are triggered when an external index, such as a rainfall during the planting season or the average yield of a specific area exceeds (or falls below) a critical value called the strike-point. Since payouts do not depend on the loss experienced by the individual insured farmer, index insurance is less susceptible to asymmetries of information. Similarly, since determining whether a payout is warranted does not require on-farm inspections, index insurance may be offered with substantially lower transaction costs. Against these advantages stands one of the primary challenges of index insurance; namely "basis risk", or the risk that a farmer suffers a loss but does not receive an insurance payout. As described by Carter (2012), some basis risk is unavoidable in index insurance, but it can be minimized by careful contract design that maximizes the correlation between the index and farmers' losses. A number of recent studies analyze the potential of index insurance to reduce poverty by enhancing households' capacity to smooth consumption in the face of weather shocks and improve both households' access to and willingness to take

[1] Skees et al. (2006) offer a detailed description of the costs and challenges of conventional contracts (multi-peril) associated to the lack and asymmetry of information.
[2] See Hazell et al. (2010) for a detailed summary of the evolution of index insurance in developing countries. Barnett et al. (2008) and Carter et al. (2014) present a summary of the pilots of index insurance in the third world.

on credit (Skees 2006; Barnett et al. 2008; Hazell et al. 2010). These authors are careful to point out, however, that the success of index-based insurance will ultimately depend on whether or not the contracts that are designed offer a significant reduction in transaction costs without prohibitively high levels of basis risk.[3]

Although high quality, empirical evidence on the impacts of index insurance is scarce, initial efforts give reasons for cautious optimism. For example, Fuchs and Wolff (2011a) find a statistically significant impact of county-level weather index insurance on maize productivity and household expenditure and income in Mexico. Elabed et al. (2014) find a positive effect of an area-yield index contract on area planted and seed investment among cotton farmers in Mali. Karlan et al. (2012) find that a rainfall-based index insurance contract has stronger effects than direct cash grants on farmers' investment levels in Ghana. Finally, Janzen and Carter (2013) show that a satellite-based index contract that measures the level of natural pasture available reduced distress sales of livestock and significantly stabilized consumption among herders in northern Kenya.

A separate strand of the literature has directly compared index versus conventional insurance in order to identify circumstances under which index insurance has the potential to perform better than conventional insurance. Miranda (1991) theoretically establishes conditions under which area yield-based index insurance would provide greater protection to farmers than conventional insurance. Through a simulation based on Kentucky soybean producers, he then concludes that, for most producers, area-yield index insurance would provide "better overall yield risk protection than individual insurance (p. 242)" since it would cover more of the systemic yield risk and it would be more sustainable than individual insurance. Similarly, Breustedt et al. (2008) find that area-yield insurance is more effective in risk reduction for wheat producers in Kazakhstan than individual-based yield insurance with a low strike yield. Research in Ecuador that will be discussed in this article also reflects the potential of area yield-based index insurance to provide farmers greater risk management than conventional insurance.

Nonetheless, despite its clear advantages, index insurance also faces important challenges; mainly the lack of information required to build an effective index that offers real protection for farmers. Binswanger-Mkhize (2012) questions the general availability of sufficient information and provides a cautionary critique of the recent shift towards index-based insurance. Binswanger-Mkhize's cautionary message is important, as there is no guarantee that sufficient quantity and quality of data will be available to design contracts of sufficiently high quality. The lack of high quality data aggravates basis risk by increasing the frequency and size of index prediction errors and reducing the correlation between farm yields and the index (Carter 2012).[4] Information in developing countries on both yields and potential weather-based indices, such as rainfall and temperatures, are often characterized by low quality, with high frequencies of missing data and short time series. This leads to a vicious cycle; data are not used for productive or effective economic purposes given its low quality, and the lack of demonstrated, valuable uses of the data discourages investment in improved data collection.

[3] Carter (2012) define basis risk as "deviations in yield experienced by the household that are not correlated by deviations in the index and that are therefore uninsured by the index insurance contract (p. 4)."
[4] Other sources of basis risk include idiosyncratic risk and inadequate choices of the geographic scale for the index (See Carter, 2012).

In light of the potential for index insurance to improve small farmers' risk management capacity, we propose a dynamic strategy in which existing data is evaluated as a starting point for getting index insurance markets off the ground. If the index contracts meet a minimum quality threshold, pilot programs could be implemented, with the expectation that additional investment would be made in expanded and improved data collection so that contract quality would improve as the quality and quantity of data grows. Given the high premium rates that insurance and reinsurance companies tend to charge in order to offer index insurance in sparse-data environments, Carter (2013) proposes a public-private reinsurance partnership in which the public sector initially provides some lower-cost reinsurance for index insurance policies. Primary responsibility for reinsurance would then pass to the private reinsurance sector as additional data is accumulated, "parameter uncertainty" is reduced and more affordable contract pricing becomes possible. Especially during the initial pilot phase when basis risk may be high, hybrid contracts that combine a weather, satellite or area-yield-based index with on-farm "audits" represent a promising strategy to compensate for initially high basis risk (Carter et al. 2014).

A primary role of government under this type of arrangement would take the form of increased investment in data collection efforts such as yield surveys and automated weather stations, and potentially investment in technologies that allow the gathering and analysis of higher volumes and variety of information (e.g. GPS, drones, hardware and software appropriate for big data) for agricultural insurance purposes. This strategy for the use of public funds to break the aforementioned vicious cycle is based on the public good nature of this type of yield and weather information and, we expect, promises to be more cost-effective and sustainable than large-scale, direct premium subsidies.

In this paper, we emphasize the potential for large-scale, government collected and/or publicly available data to effectively enhance insurance availability and risk management for smallholder farmers by enabling the design and implementation of index insurance contracts. We do this by summarizing three case studies that utilize three different types of indices, and thus require different types of data. The first case study is Mexico's experience with catastrophic, weather-based index insurance. The second is the Index-Based Livestock Insurance (IBLI) in Kenya, a contract designed with a combination of livestock mortality data and satellite data that measures the vegetative density and thus caloric availability to animals of natural pasture. The third case study presents results of a research project in Ecuador where the potential performance of a hypothetical area yield-based index insurance contract was compared to the actual performance of an existing conventional insurance contract. The potential for and challenges facing the use of big data to improve the quality of index insurance contracts and extend index insurance markets in the future is also addressed in this paper.

The paper is structured as follows. Section two briefly describes the different types of indices that are most commonly used and the advantages and disadvantages of each. The three case studies are presented in Sections three, four and five. Section six links the potentials for big data application to index insurance in developing countries, including examples in the context of the researched cases. The final section concludes.

Types of Index Insurance

The primary objective of index insurance is to protect farmers against covariate risk, or risk that drives fluctuations in average yield of farmers in a given region. The ideal index insurance contract would thus be perfectly correlated with average, or area, yields in the contract area. Based on this goal, we can classify indices into two general classes: *indirect and direct*. Indirect indices use data from weather stations or satellites to generate indirect estimates of average yields in the contract area. Examples of indirect indices include various functions of weather phenomena, such as cumulative rainfall during planting season, and the Normalized Difference Vegetative Index (NDVI), which uses satellite images to estimate the density of pasture available to livestock. An important challenge of indirect indices is understanding the relationship between the weather event (or satellite imagery) that generates the data (i.e., millimeters of rainfall) and average yield and then to design the index to best capture this relationship. In many cases, this requires a good agronomic model of crop growth for the specific insured crops.

The potentially large advantage of indirect indices is the relatively low cost of index measurement which, in many cases, simply requires taking measurements from weather stations or downloading publically available satellite data from the internet. However, in practice, acquiring and assembling data underlying indirect indices may imply some costs. First, there may exist fixed costs to design the index (including research to identify the strongest relationship between the available weather or satellite data and yields). Second, the information may not be freely available. Although it is typically the public sector that collects and manages weather data, the institutions that manage the data may charge for their access. In the case of satellite data, experts often need to be hired to convert the raw data into a form that is usable for the purpose of an index. Finally, installing and maintaining weather stations implies a non-negligible cost.

An important disadvantage of indirect indices is that, if the index only captures one of the multiple sources of covariate risk, then basis risk may be significant. For example, coffee production is adversely affected by excess rainfall in the flowering period as well as by a deficit of solar radiation during the period of fruit growth. If the index is based solely on rainfall, for example, the contract will likely suffer from significant basis risk.

Direct indices, in contrast, directly estimate average, or area, yield in the contract area, typically through a production survey or plant cuttings of randomly selected plots.[5] Precisely because they directly measure average yields, direct indices take into account all of the potential sources of covariate risk that affect average production levels and, as a result, will be characterized by lower levels of basis risk than indirect, weather-based indices. A second advantage of direct indices is that they are typically more intuitive, transparent and easy to understand for farmers compared to indirect indices.

The main disadvantage of direct indices is the greater cost associated with directly measuring average yields through farmer surveys or crop cuttings. This cost will depend on various factors, including the sample size needed to achieve a specified level of statistical precision of the average yield estimate as well as the spatial dispersion of and ease of access to the sampled plots. Another important factor affecting the cost of direct indices is the existence (or not) of a national agricultural production survey upon which area yields can be estimated at a sufficiently disaggregated scale.

Breustedt et al. (2008) show for Kazakhstan the ability of area yield insurance to provide more risk reduction than weather-based index insurance. The benefits of area yield index

[5] In the case of cattle, livestock mortality measured via survey is an example of a direct index.

insurance are also noticed by Carter et al. (2007), who compare the performance of area yield and weather based index insurance for farmers and lenders in Peru.

Catastrophic Weather-Based Index Insurance: The Mexican Case

Mexico is among the countries with the most advanced agricultural insurance programs in the world, including several different types of index insurance programs since 2003.[6] Mexico was one of the first countries to implement a catastrophic weather-based index insurance program (WII). This program has grown rapidly and is now one of the largest worldwide (Fuchs and Wolff 2011a). The contract uses a rainfall index to protect small farmers growing maize, sorghum, beans and wheat, against droughts, the main cause of agricultural catastrophes in Mexico (AGROASEMEX 2006). Below we describe the data used for the WII contract, details about the contract's implementation and its effect on farmer behavior and poverty reduction.

The Data

Mexico's WII contract uses publicly available rainfall and temperature data from the government's network of weather stations. These weather data, along with data on soil types from detailed soil maps, are fed into a dynamic crop model that allows estimation of the relationship between yields and the specific weather phenomenon.[7] The model allows AGROASEMEX, the Mexico's parastatal insurance and re-insurance company to estimate crop yields in regular circumstances and yields when a deficit of precipitation is the primary limiting factor.[8] Thresholds are established for each stage of the crop's vegetative cycle such that when rainfall is below the threshold level, farmers are highly likely to suffer significant yield losses (AGROASEMEX 2006). WII also takes into consideration critical temperature levels that indicate severe loss (AGROASEMEX 2015).

Although the Mexican government manages over 5,000 weather stations, relatively few of them are suitable for WII (Fuchs and Wolff 2011a).[9] Many stations are ruled out because they are not located close enough to areas where the insurable crops are grown. In addition, AGROASEMEX and its international reinsurers require that all weather stations used to develop the index comply with international quality standards. Specifically, the data from a station must be available for at least twenty-five continuous years, with a maximum of 10% missing or invalid data. In addition, the stations must allow timely reading of the climatic data so that contract implementation and potential payouts to farmers are not delayed (AGROASEMEX 2006).[10]

[6] Other types of index insurance implemented by AGROASEMEX include NDVI and area yield index insurance.
[7] By isolating climatic events from other factors that affect production, the model performs simulations that allow the calculation of dry matter under both potential and limiting climatic conditions. The main components of the model are the physiological age of the crop, the raw assimilation of CO_2 and dry matter distribution (AGROASEMEX 2006).
[8] Since 2013 a private insurance company is also offering WII together with AGROASEMEX (FAO, 2014).
[9] By 2006, 297 weather stations were participating in Mexico's WII (AGROASEMEX, 2006).
[10] Historical data is used to estimate the probability distribution function of the index, which is crucial for designing the contract. Periodic data is required for the operation of the insurance contract; that is, to determine whether or not a payment is due, and the amount of the covered loss.

As acknowledged by AGROASEMEX (2006), expansion of the area eligible for catastrophic insurance coverage is limited by the lack of data of sufficient quantity and quality. To this end, this company has been working on improving the quality of data generated by the weather stations. This effort is expected to lead to premium reductions by the international re-insurance companies.

Implementation of the Contract

The general goals of the WII contract are to protect low-income farmers from severe climatic shocks and help state and local governments to more efficiently manage the risk of catastrophic losses among the rural population (AGROASEMEX 2006). The premium is fully subsidized with the federal government assuming 80% of the premium cost while state governments pay the remaining 20%. For poorer states the arrangement is 90% (federal) – 10% (state). As a result of the WII program, the federal government has been able to reduce post-catastrophe direct payments to state and local governments; federal government participation fell from 70% to 50% of all direct payments to farmers in 2013 (FAO 2014).

The program started in 2003, with a pilot offering in the state of Guanajuato. Based on its initial success, the program has expanded to vulnerable areas of all thirty-two Mexican states (FAO 2014). The area covered by the program grew remarkably fast, from around 100,000 hectares in 2003 to 12 million hectares in 2013. Total indemnity payments to farmers between 2003 and 2013 exceeded USD 290 million (Ibid).

Each year, states propose to the federal government the specific counties and the number of hectares within each county to be insured before the beginning of the planting season (January to March).[11] When a catastrophic event occurs (rainfall or temperature levels surpassing maximum thresholds or falling below minimum thresholds) indemnity payments are received by the state governments and then distributed to farmers that meet established eligibility criteria (in general, less than 20 hectares) in the insured regions.[12] The beneficiaries are identified only when indemnity payments are due (FAO 2014).

In order for the WII program to have its intended consequences, for example of increasing investment levels by small-holders, eligible farmers in the insured areas should know that they are insured and should receive support in case of a climatic shock. It is also important that the farmers understand that any indemnity payments they receive are the results of an established insurance market instead of political or other types of interests. In order to promote awareness of coverage among eligible farmers, the government seeks to inform them about the insurance through regional offices of official programs such as PROCAMPO. In addition, the Ministry of Agriculture contracts external evaluations of the program and includes among program indicators farmers' familiarity with the insurance. These outreach efforts appear quite successful; according to the 2010 evaluation (Universidad Autónoma Chapingo 2010), 95.5% of the covered population knew about the program and 99.9% of beneficiaries could identify the specific climatic shock associated with the payouts they received.

[11] In addition, a complementary insurance policy can be contracted directly by the Ministry of Agriculture for uninsured vulnerable areas. In this case, the areas to be insured are determined in May and state governments can opt to pay their corresponding portion of the premium if they wish to receive indemnity payments directly.
[12] The states can also, after federal authorization, use the funds in alternative ways, such as the re-construction of infrastructure that has been affected as a result of the climatic shock (FAO 2014).

Results on Farmer Behavior and Poverty Reduction

We begin by summarizing several concerns related to contract design expressed by Fuchs and Wolff (2011b), who analyze the Mexican WII contract in detail. First, the current practice of basing the index on cumulative rainfall within a period should be complemented with the variance of rain during the period because yields are affected not only by the total amount of rainfall but also the number of days of rain and the timing of rainfall. Second, thresholds of rain millimeters below which indemnities must be paid should be readjusted over time (thresholds have not been changed since the beginning of the program) so as to avoid inhibiting investment in research for the development of drought resistance seeds. Finally, the authors identify several potential negative spillover effects of the WII contract. These effects include the discouragement of investment in irrigation infrastructure (WII is only available in rainfed areas) and of crop diversification since relatively few crops beyond maize are covered.

However, the same authors (Fuchs and Wolff 2011a) performed an in-depth analysis of the effects of WII on maize productivity, per-capita income and expenditure, and farm-level risk management from 2003 to 2008. Comparing initially treated counties with counties later covered by WII and counties never treated with WII, the authors find a positive effect on maize productivity (6%), which reveals an ex-ante response; that is the index insurance induced farmers to increase input intensity and improved production techniques. The authors also found positive spillover effects: the area planted with maize decreased by 8%, with an expansion in the area devoted to more profitable, commercial crops. This finding mitigates the concern mentioned above about crop overspecialization. Finally, the authors point out that credit constraints were likely reduced by the WII program, a result consistent with the intensification of production and increase in yields.

Index-Based Livestock Insurance (IBLI) in Kenya

IBLI constitutes the first livestock insurance in Africa (Mude 2014).[13] It was designed by the International Livestock Research Institute (ILRI) with Cornell University, Syracuse University and the BASIS Research Consortium as technical partners. IBLI was introduced in northern Kenya in 2010 and then in Ethiopia in 2012. IBLI targets pastoralist households in arid and semi-arid lands. In Kenya, for example, more than three million households depend on livestock as their primary, or in many cases only, asset and livestock generate more than 60% of their income (Chantarat et al. 2013). Severe drought, which is becoming increasingly frequent and unpredictable, is the main cause of livestock mortality in this region and causes significant hardship for pastoralist households. In Kenya, the program started in Marsabit District, where high-quality historical livestock mortality data were available. Based on encouraging findings from impact evaluations in Marsabit, the program was extended to four other districts between 2013 and 2015 (Jensen et al. 2015).

In this section we briefly describe the data used to design the original contract in Kenya, the contract implementation and the main results noted in the impact evaluations.

[13] The policy covers the primary forms of livestock in the region including goats, sheep, cattle and camels.

The Data for IBLI

The IBLI contract was developed using two types of historical data sets: one tracking losses to the primary asset to be insured and one allowing construction of potential indices correlated with these losses. The first data set contains household-level livestock mortality collected via a monthly survey conducted in Marsabit District by the Kenyan government's Arid Land Resource Management Program (ALRMP). These livestock mortality data were collected between 2000 and 2008, allowing the construction of a sample of 112 season-specific observations of average livestock mortality rates across smaller geographic sub-regions within the district (Chantarat et al. 2013). It is important to note, however, that the ALRMP data cannot be used to implement a widely available index insurance contract based on directly measured average mortality rates because the sample is clustered spatially and does not have sufficiently broad coverage across space.

The second data contains the Normalized Difference Vegetation Index (NDVI), an indicator of vegetation density, computed by the National Aeronautical and Space Administration (NASA) using satellite data collected by the National Oceanic and Atmospheric Administration of the United States (NOAA). NDVI is the basis for constructing the contract's index with the logic that vegetative density falls significantly under severe drought as the natural pasture and forage that the pastoralists rely on to feed their livestock declines. The NDVI data are characterized by high spatial resolution (8 km2) and are been generated at a 10–16 day frequency. These data, which are collected by US institutions and freely available, have reliably provided information about Africa's pastureland since 1981 (Mude et al. 2009; Chantarat et al. 2013).

In order to design the IBLI contract, researchers estimated the relationship between various potential NDVI indices and livestock mortality. The index that was eventually selected was the best predictor of severe mortality incidents. IBLI represents an important step forward in the design of index insurance contracts in the developing world. It represents the first index-insurance contract developed on the basis of household-level panel data. These data permitted both careful estimation of the relationship between a range of alternative NDVI-based indices and herd mortality and, importantly, the ex-ante evaluation of the magnitude of basis risk associated with each potential index. This approach, while demanding in terms of data and human capital, is crucial to identify contract structures that minimize basis risk and thus provide maximum value for the insured households (Mude et al. 2009).

The Contract Implementation

In addition to careful contract design, the implementation of IBLI was also carefully thought-through to allow for a rigorous evaluation of the program in order to generate learning about welfare impacts on households and lessons that would help improve the design of the contract itself. The evaluation implied adopting an experimental design of the contract's implementation, including randomly assigned price incentives and extension/educational campaigns. Baseline data on key characteristics of a random sample of households was gathered prior to the initial offering of the IBLI contract in Marsabit. A similar household survey is applied annually to the same households in order to evaluate the impact of this contract on pastoralists' well-being, perform a rigorous analysis of basis risk and understand what motivates pastoralists to purchase the insurance (Jensen et al. 2015). Given the existence of an unconditional cash transfer program in the same district since 2009, the Hunger Safety Net Program (HSNP), the experimental design also allowed for an opportunity cost analysis of the use of public funds in IBLI by comparing its benefit/cost ratio to that of the HSNP (Jensen et al. 2015; Mude et al. 2010).

IBLI's implementation was facilitated by the presence of the HSNP since the cash transfer program had already created the infrastructure for delivering the cash aid in the same remote areas covered by IBLI. Specifically, Equity Bank made a large investment in wireless portable devices (point of sale software or POS system), which allowed to collect IBLI's premium and distribute indemnity payments, thus reducing the need for insurance agents to carry cash and greatly reducing the transactions costs of the insurance (Mude et al. 2009).

Northern Kenya has a bimodal rainfall distribution and two associated growing seasons. IBLI contracts are offered for both seasons (long rain-long dry and short rain-short dry periods). The contracts are sold approximately two months before the beginning of each season, and predicted livestock mortality is announced at the end of each season. The predicted livestock mortality rates are generated by plugging the value of the NDVI index for the season into the livestock mortality model described above. Indemnity payments are made if the predicted livestock mortality exceeds the strike-point of 15%. Payouts to farmers are equal to the difference between the predicted mortality rate and the strike point, times the value of the insured herd. This value, in turn, is the number tropical livestock units (TLU)[14] the household chose to insure times a pre-agreed value per TLU (Chantarat et al. 2013; Mude et al. 2009).

The Results

Researchers have evaluated IBLI based on a number of outcomes including pastoralists' demand for the product, as well as IBLI's impacts on pastoralist's investment behavior and consumption, income and poverty levels. As noted in Jensen et al (2015), there has been strong and growing demand for IBLI since the beginning of the program, with the percentage of eligible households purchasing the insurance increasing from 30% to close to 50% over the first three years. On the other hand, there has also been a growing rate of dis-adoption, that is, households who had purchased the product at least once but that did not buy it any further (from about 20% to close to 40%). Potential reasons for the observed dis-adoption rates include: discouragement due to absence of indemnity payments early on and logistical issues complicating product sales. Other variables found to have a strong influence on demand for IBLI are the product's price, financial liquidity of the household, the level of covariate risk in the region and individuals' predictions about rangeland conditions, as well as the availability of alternative coping strategies (Jensen et al. 2015; Chantarat et al. 2009).

Ex–ante responses to IBLI have included a decrease in herd size,[15] greater investment in veterinary and vaccination services for the livestock, and other changes in production strategies leading to increased milk productivity and improved household income and nutrition (Jensen et al. 2015).

The catastrophic drought in the Horn of Africa in 2011, triggered the first indemnity payouts. A study by Janzen and Carter (2013) identified the ex-post impacts of IBLI on distress

[14] The TLU measure allows for aggregation of different species based on their average metabolic weight. That way, 1 TLU = 1 cattle = 0.7 camels = 10 goats or sheep (Chantarat et al. 2013).

[15] Since households tend to hold assets as precautionary savings, a reduction in herd size and a corresponding increase in consumption can occur as a response to the availability of insurance. This can be expected for households above a critical asset threshold (Janzen et al. 2013).

livestock sales and food consumption. Since their survey was performed at the time of the payouts, they asked households about the way they had been coping with the drought during the three months prior to the survey (Q3), and about the ways they were planning to cope with the drought during the three months after the survey (Q4). Compared to uninsured households, the authors found that insured households were, on average, thirty-six percentage points less likely to resort to livestock sales and twenty-five percentage points less likely to decrease the number of daily meals during Q4.

Interestingly, however, the researchers find a heterogeneity of anticipated reactions to insurance payouts based on an identified critical asset threshold. Economic theory on the accumulation of productive assets predicts that relatively asset rich households will tend to reduce their assets in the event of a shock so as to smooth consumption, while asset poor households will instead hold on to their assets, sacrificing food intake, so as to preserve their limited income-generating capacity. The results of this study support the theory and show positive effects of IBLI on these two types of households. That is, asset rich households were significantly less likely to sell assets during Q4 compared to uninsured ones (this impact was statistically insignificant for insured poor households), hence helping these families to preserve their source of future income.

On the other hand, asset poor households were found less likely to reduce the number of meals thanks to IBLI's payout (this impact was statistically insignificant for insured richer households). This finding implies that IBLI led to a reduction in malnutrition in this food insecure region. Janzen and Carter (2013) also found that IBLI positively impacted asset poor households in Q3, as they had tended to rely less on coping strategies that would destabilize consumption because they expected a payout from IBLI.

Another noted impact of IBLI has been a 33% reduction in food aid needed for northern Kenya (Malone 2014). The positive results obtained from IBLI have encouraged its expansion to other Kenyan districts and also its evolution to be able to rely only on NDVI data so as to be offered in areas with lack of data on livestock mortality (IBLI's website 2015).

The "Shadow" Area - Yield Index Insurance in Ecuador

Ecuador enjoys a privileged situation with respect to the availability of agricultural yield data. Specifically, since 2000, the government of Ecuador has administered the Continuous Area and Agricultural Production Survey, known by its Spanish acronym ESPAC. The ESPAC is a national survey that collects data on area planted and yields and thus can potentially serve as the basis for an area yield index. Unfortunately, while a relatively large quantity of high quality yield data exist, the same is not true with respect to weather data in Ecuador. There are relatively few meteorological stations, including only two automated stations, and the data that do exist are insufficient to design index-based contracts.

In order to explore the viability of index insurance for small-holders in Ecuador, the authors carried out a research project between 2010 and 2014. This project included the design of a hypothetical, or "shadow", area yield index insurance contract and an analysis of the degree to which this shadow contract, had it been available, would have improved the income and consumption smoothing capacity of maize and rice farmers in three separate cantons.[16] The performance of the shadow index contract was then compared to that of the actually existing, conventional insurance contract that was offered in the same areas. The provision of significant premium subsidies for this conventional contract has been the primary government policy to strengthen crop insurance markets since 2010.

The analysis was based on data collected from a panel of 1,000 maize and rice farmers surveyed in 2011 and 2012 in two of the main maize growing cantons (El Empalme and Celica) and one rice growing canton (Daule). All sample farmers were insured under the conventional insurance contract, primarily because they had taken out loans from the formal banking sector, which has increasingly required farmers to hold crop insurance as a condition for credit access.

In the remainder of this section, we describe the ESPAC yield data, the construction of index insurance contract areas and briefly discuss results of the comparison of the two types of contracts (index vs. conventional) in terms of their ability to shield farmer's income from yield risk.

The Historical Data: The ESPAC Yield Survey

The ESPAC is a survey administered annually by Ecuador's National Census and Statistics Bureau (INEC), with the primary objective of generating province-level production and yield estimates for the country's primary crops. The ESPAC uses the 2000 agricultural census as its sample frame. The census divided the country's cultivable land into Primary Sampling Units (PSM), which are contiguous areas of approximately ten square kilometers that are homogeneous in terms of agro-ecological conditions. Each PSU, in turn, was sub-divided into smaller sampling units called Sample Segments (SS) of approximately two square kilometers. In 2002, from the universe of 69,272 SS's throughout the country, INEC randomly selected 2,000 for inclusion in the ESPAC sample. Within these chosen SS's, INEC applies the annual ESPAC survey, which collects information on land use, area planted and production, for all plots within each SS.

Since 2002, INEC has carried out the ESPAC in the same 2,000 SS's each year.[17] Including the data collected from these same SS's in the 2000 census, the ESPAC data set consists of a twelve-year panel of all plots within these 2,000 SS's (i.e., 2000, 2002–2012).[18] These data, collected as part of the government's annual yields survey, permit us to design the "shadow" index contract.

Definition of Contract Areas: Clusters of Sample Segments

With the large government-collected historical yield data in hand, the first step was to design the index insurance contract. Given the large quantity, both cross sectional (i.e., many plots per season) and over time (i.e., from 2000–2012) and high quality of yield data available, we

[16] Canton is the administrative unit below the province in Ecuador.
[17] 2006 was the only exception. In that year, due to a one-time budget expansion, the ESPAC was carried out in 3,610 SMs.
[18] Given that our objective was to construct a shadow index contract for corn and rice, we restricted attention to those SS in which at least one plot was planted in the relevant crop (rice in Daule and corn in El Empalme and Celica) in each year.

constructed a direct area-yield index for our "shadow" contract. A first step in operationalizing the shadow contract is to define the contract area, or the geographic areas in which average, or area, yield is calculated. Once the contract areas are defined, the historic data from the ESPAC yield survey can be used to estimate the probability distribution function of area yield for each contract area.

There are several options for defining the contract areas. At one extreme, we could define the entire canton as a single contract area. Under this option, we would combine the data from all of the SS's within the canton to estimate the average yield in the canton. This option would be attractive if the canton was characterized by a high degree of homogeneity in terms of agro-climatic conditions. Unfortunately, the cantons in our study (and in general in Ecuador) are characterized by a high degree of internal heterogeneity and, as a result, this option would result in a high degree of basis risk.

At the other extreme, we could define one contract area for each SS. While this option would reduce the level of basis risk, it suffers from two potentially serious problems. First, since there are relatively few (between 10–50) plots in each SM, this option would generate an estimate of average yield that is likely to have relatively low statistical precision (i.e., relatively large confidence interval around the estimate). The second concern is more operational since this option would imply defining and executing a different contract for each SS and, as a consequence, would increase the operating costs of the insurance policy. In the case of El Empalme, for example, this option would imply defining thirty-six separate contracts.

The option we chose for this exercise represents a middle ground in terms of spatial aggregation. Specifically, in each canton, we use the statistical technique of cluster analysis to group together similar SS's into a small number of contract areas. We defined clusters that maximize the co-movement between average yields across SM's over the historical period for which we have data from the ESPAC survey: 2000–2012. The result of this statistical procedure was the definition of three contract areas in each of the cantons of El Empalme and Daule and two in Celica. While in some cases the clustered contract areas include SM's that are quite spatially concentrated, in other cases they include SM's that are more distant from each other but that share certain characteristics (for example altitude or bordering a river) that imply a high degree of co-movement in average yields.

In order to evaluate the hypothetical performance of the shadow index insurance contract for our sample, we assigned each plot operated by our 1000 sample maize and rice farmers to the contract area associated with the nearest ESPAC SS.

Results: Comparative Performance of Index versus Conventional Insurance

In order to make a meaningful comparison across the two types of contracts, we chose a strike-point for the shadow index contract such that its price would be the same as that of the actually existing conventional contract. We thus answer the question: Which type of contract offers greater protection f*or a given cost*? Our comparison is based on two alternative measures that influence the degree to which the insurance contract affects farmers' end-of-season income after accounting for premiums paid and indemnities payments received. We are particularly interested in the success of the insurance contracts in maintaining a minimum level of earnings for those farmers who suffered the greatest losses, which is to say those who are in the lower deciles of the yield distribution. The two measures are:

- The net revenues received by the farmers defined as gross revenues minus the premium payment plus any indemnity payment received,
- The fraction of farmers in each decile of the yield distribution who receive an indemnity payment.

For brevity, the focus of these findings is for maize farmers. Ideally, we would like to have a long time series over which to compare the performance of the two contracts. However, we only have information on two years (2011 and 2012). Fortunately, these two years were very different in terms of climate and agricultural production, thus providing a useful window through which to evaluate the quality of the contracts.

Observations from the two years were divided into ten yield deciles. Each decile was then compared for the following three situations: 1) Net revenues per hectare under the "shadow" contract (i.e., gross revenues minus any indemnity payment that would have been received under the index contract scheme minus the hypothetical index premium); 2) Net revenues per hectare if they had no insurance and; 3) Net revenues per hectare under the actual conventional insurance scheme (i.e., farmers' actual net revenues).

It was found that farmers in the lowest yield decile in both 2011 and 2012, the net revenue per hectare was $217 under the existing conventional insurance scheme. Net revenue per hectare would have been would have fallen to $133 under the no-insurance scenario; and would have been $329 under the "shadow" index contract. This result of greater protection offered by the shadow index insurance contract than the conventional contract held over the bottom five deciles of the yield distribution.[19]

This better protection offered by the index contract for the bottom of the yield distribution can be seen clearly in Figure 1. For farmers in the first five deciles—who suffered the greatest losses and needed the largest indemnity payments—the net payment of the index insurance contract (indemnity minus premium) would have been about two times as high as the net payment farmers actually received from the conventional insurance contract. This difference does not necessarily indicate a failure of the conventional insurance, rather it reflects the higher operating costs and the less generous level of coverage. Stated another way, for the same cost, index insurance offers significantly more protection against yield driven income fluctuations.

Turning to the frequency of receiving indemnity payments, the performance of the two contracts is similar. For the bottom yield decile, a bit more than 90% of farmers would have received a payment under index insurance, while slightly below 90% received a payment from the existing conventional insurance. Once again, index insurance dominates the conventional insurance in the first five deciles. In the highest deciles, the realized losses are likely more idiosyncratic and do not reflect events, such as drought, that result in massive losses. In these deciles, we can see the existence of basis risk with the index insurance, although it is clear from Figure 1 that the payments by the conventional insurance are small on average.

In global terms we see that, for the first five deciles the average income of farmers is higher with both the index and conventional insurance contracts than without any insurance.

[19] The maize farmers from the seventh decile on had relatively good yields. As is reasonable, these farmers would have been slightly better off without insurance than with either of the two insurance types.

Nonetheless, we observe that the index insurance contract consistently offers greater protection than the conventional insurance across each of the bottom five deciles. The impact of index insurance is indeed greatest where it is most needed; for the first decile, the index insurance would have increased income by $200 per hectare, while the difference is only $100 for the fourth decile. On the other hand, we observe that the conventional insurance is slightly better than index insurance for the highest deciles (at the most it offers $10 per hectare on average).

Although these results show clear advantages for the area yield-based index insurance developed using the ESPAC data, we need to be cautious given that these results were based on only two years of information, one of which was characterized by a catastrophic drought for maize producers. It is precisely in that year that the protection offered by the index insurance would have been much greater, compared to the more "normal" year in which the losses were likely more the result of idiosyncratic factors, or more routine shocks, which tend to affect few people. In this latter case, conventional insurance provided slightly better protection.[20]

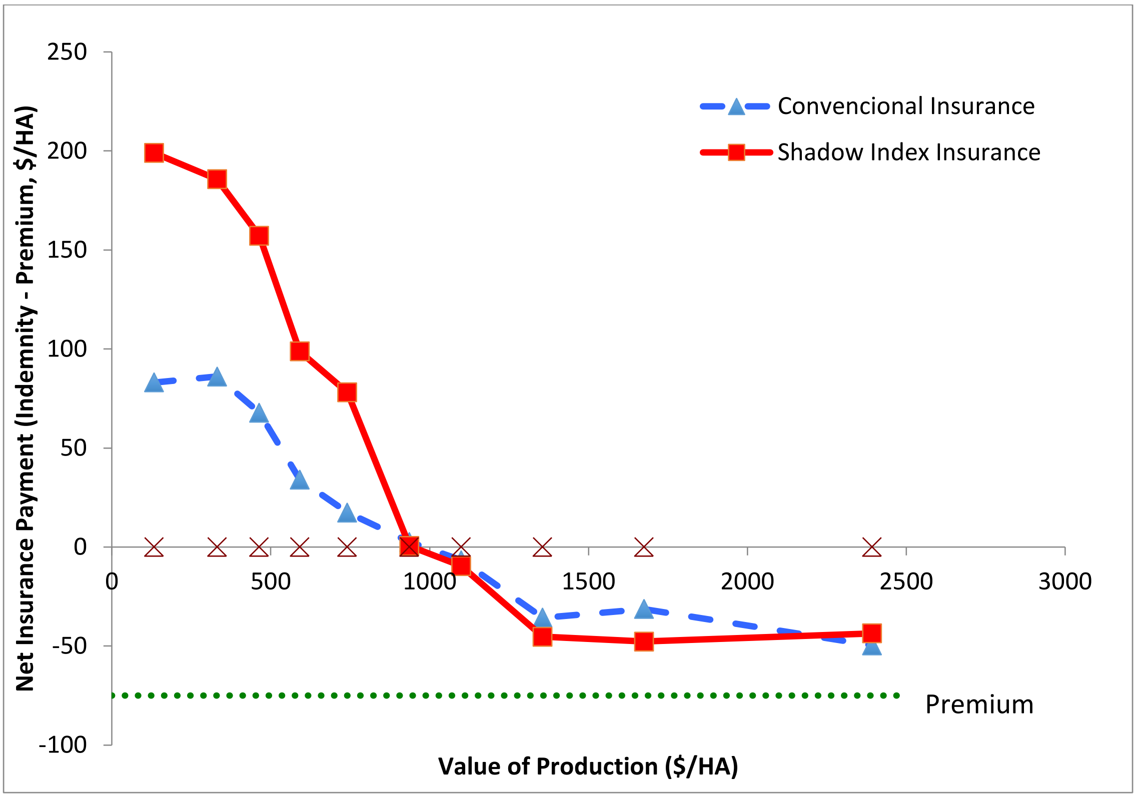

Figure 1. Net payments received by maize producers, 2011 and 2012

Notes. The horizontal axis represents the value of production for the various deciles in dollars per hectare. The 'x' on this axis show the position of the various deciles. The solid red line shows the value of the indemnity minus the cost of the premium for the index insurance. Without any indemnity payment, the line would be at the level of -$75 per hectare (the value of the premium). The blue dashed-line shows the same net impact on income for farmers in the various deciles for the conventional insurance.

[20] About 25% of farmers received payments under the conventional insurance in 2012. These payments were small on average and did not reach the level of the premium in any decile. For both contracts, this is what would be expected in a year without large losses.

Importantly, our study shows that Ecuador's national yield survey (ESPAC) could likely serve as the basis for the development of an area yield index insurance policy that, dollar for dollar, offers better protection for small and medium farmers compared to the existing conventional insurance policy. The area yield index insurance contract offers the potential for better protection not just to individual farmers, but also to protect the portfolios of financial institutions with significant agricultural loan portfolios and, potentially, to local governments in regions with high dependence on agriculture against climate-related disasters. Supporting this type of contract would also imply a more cost-effective use of public funds compared to the current conventional insurance subsidy. The governmental institution in charge of the ESPAC is currently in the process of updating and expanding that survey, a policy that provides a unique opportunity to develop a high quality area yield index insurance market in Ecuador.

Big Data and its potential for Index Insurance

Our discussion suggests that index insurance holds the potential to improve the risk management capacity of small-holder farmers in developing countries and could play an important role in reducing poverty and enhancing rural development. While significant strides have been made, index insurance markets remain thin and, and even where it is available, demand is relatively low. Realizing the full potential of index insurance, through expanded coverage and improved contract design, requires creativity and innovation. Although challenging, increased incorporation of big data in the design, execution and evaluation of index insurance offers an attractive area for innovation and creative thinking.

Big data derives from technological applications, such as cell phone apps, satellite and radar-based imaging and drone-based imaging, that generate unstructured data in high volumes and at high frequency. These data, if structured and analyzed, can be useful for a variety of purposes including marketing, health care, agricultural extension and support, climate predictions, and national security. Structuring and analyzing these data is, however, not an easy task. It requires powerful analytical tools that allow rapid, high-frequency analysis and high quality human resources with sufficient statistical knowledge and the ability to work with these tools and interpret the results (Sonka 2014; Manyika et al. 2011; da Silva 2016).

A primary challenge to generating and using big data in developing countries is insufficient access to technology, particularly the requisite computing power, internet bandwidth and sophisticated software (da Silva 2016). Another major challenge is the lack of analysts with the skills described above. While fully overcoming these limitations will require time and long term investment in human capital, a number of strategies, including developing key public-private partnerships, could be implemented in the short term in order to speed developing countries' capacity to benefit from big data.

Initiatives like the recent partnership between Google and FAO, aimed at facilitating developing countries' access to satellite data in order to improve their capacity to plan and monitor the use of their natural resources, represents one example of this type of partnership (FAO 2016). Through this partnership, FAO's offices in member countries can request training of their staff and technical experts to use Google technology to access and analyze satellite data for identified needs such as monitoring deforestation rates, carbon sequestration, and agricultural yields. This type of collaboration can help public and private institutions in developing countries access and effectively use the copious amounts of meteorological and agricultural data available through big data to both improve the quality of existing index insurance contracts (i.e., reducing basis risk) and expand coverage of index insurance to currently unserved areas. The Radar-based remote sensing Information and Insurance for Crops in Emerging economies (RIICE) project is one example of a collaboration that is putting these ideas into practice. Five partners[21] have joined together to make use of radar-based remote sensing technology (or Synthetic Aperture Radar–SAR) to provide information on rice growth in Asian countries to enhance food security and strengthen insurance markets (RIICE 2016; Holecz et al. 2013). RIICE takes advantage of data collected by radar sensors in satellites of the European Space Agency and other providers. Because these sensors can detect vegetation growth without the need of direct observation (i.e., they are not restricted by cloud cover), this collaboration permits the use of remote sensing data in the design of index contracts in areas, such as the highland and jungle regions of Ecuador, where dense cloud cover throughout the year has previously ruled out the development of satellite based insurance contracts. Local public sectors play a key role in the partnership, which has been implemented in parts of six Asian countries since 2012, by participating in product development and gathering terrestrial data for validation or "ground truthing" of the satellite data (Holecz et al. 2013). Based on these validation exercises, the accuracy of the estimates of planted area and rice yields generated by the RIICE project is significantly higher than the conventional estimates generated by national statistical offices.

Another important advantage of the RIICE estimates is the speed of generating actionable data. For example, RICIE estimates of crop yields or crop losses are available within several days, thus allowing governments or insurance companies to respond to catastrophes in a much more timely manner (ASEAN SAS 2016). This project is now in its second stage (2015–2018), which includes the piloting of national crop insurance programs (Ibid).

In a related partnership, the Global Index Insurance Facility (GIIF) of the World Bank and AXA Corporate Solutions (AXA CS) have joined forces to promote the use of big data as a means of extending weather index insurance to regions that were previously uninsurable because of low quality or lack of weather data. Researchers in this partnership are facilitating government and private insurance sector access to and management of satellite data in order to generate higher quality (lower basis risk) weather index insurance contracts compared to contracts based on more limited data from meteorological stations (AXA 2015).

A range of additional options in the form of new technological platforms and devices exist to promote the generation and use of big data in index insurance. One particularly promising example is the use of drones to generate high quality yield data at a spatial resolution that is sufficiently high to write area yield index contracts. For example, in the case of Ecuador, implementing an area-yield index insurance contract using a survey like ESPAC could be complemented by the use of drones, which can provide high quality images that permit precise monitoring of crop development throughout the agricultural season. From the images, data can be gathered and processed to support ESPAC's findings and to generate feedback for improving contract design, for example by providing an "audit" in cases where a high percentage of farmers within a contract area suffer a loss but the insurance contract, according to the value of the index, would not normally pay out. In the long run, the use of drones could potentially serve as the primary means of generating yield data for a range of purposes, including the development and implementation of index insurance contracts.

[21] The five partners are the German Development Cooperation, the Swiss Agency for Development and Cooperation, the International Rice Research Institute, the Allianz Re insurance company, and Sarmap, a software provider.

While big data presents multiple possibilities for designing better insurance contracts and offering contracts where they were previously infeasible, it can also facilitate the implementation, monitoring and evaluation of index insurance programs. In the case of Mexico described above, for instance, the development of mobile money or "electronic wallets" with which farmers can carry out transactions through their cellphones, can be used to transfer indemnity payments to farmers in remote areas (and collect insurance premiums from farmers if it were the case), thereby dramatically reducing the transaction costs associated with implementing insurance. The big data generated by these transactions could also be used to monitor how the indemnity payments received are spent. E-wallets have been successfully introduced in a number of low-income countries including Nigeria—for the transfer of government subsidies (Akinboro 2014)—and Kenya—for microfinance-loan repayments (The Economist 2013). By allowing and recording millions of transactions in the rural sector, big data can be analyzed to gain a better understanding of how access to insurance affects key farmer behavior such as the purchase of improved seeds and fertilizer as well as household's consumption patterns. Cellphones can also be used to notify farmers about the availability of insurance programs and educate farmers about the costs and benefits of insurance so that they make informed demand decisions. The GPS location of cellphone holders can also help governments and insurance providers monitor the number of policy holders and program beneficiaries in affected locations and thus potentially monitor disaster occurrence and relief by region.

Kenya, the home of the IBLI program discussed above, is a global leader in mobile money (The Economist 2013). In Kenya, however, a number of challenges currently limit the spread and use of e-wallets, including limited access to cellphones and energy for charging the phones, as well as limited availability of mobile money network agents (Hanson 2014). These limitations are being resolved with time (Ibid), suggesting a tremendous potential for cellphones and their associated rapidly expanding services, such as mobile money, to promote the deepening of financial services, such as credit, savings and insurance via big data. In the specific case of IBLI, monitoring the use of indemnity payments through e-wallets may prove to be a valuable part of the impact evaluation strategy in the near future.

Also important to note is, as observed by da Silva (2016), the potentially important role of cooperatives for data access and data collection, especially in the context of small farmers. The organization of small farmers may both facilitate technology adoption as well as encourage the exchange of information both among farmers and between them and national research institutes or public/private service providers.

Conclusions

This paper has emphasized the key role of publicly available weather and agricultural yield data in the design of index-based insurance schemes for small-holder farmers in developing countries; precisely the segment of the rural population that is almost universally uninsured and for whom covariate risk can create and perpetuate poverty traps.

The Mexican and Kenyan cases summarized here show how index insurance has helped poor farmers by encouraging more efficient productive behavior and by reducing the use of costly ex-post risk coping strategies such as asset depletion or consumption destabilization. These benefits have led to higher per-capita income and to a reduction in malnutrition.

The Ecuadorian case also illustrated the potential of index insurance to smooth farmers' income in the face of covariate shocks such as droughts. Indeed the shadow index contract developed by the authors performed more favorably (albeit under hypothetical circumstances) than conventional named-peril insurance contracts available to farmers (in the real world). These results suggest that the development of area-yield based index insurance in Ecuador would likely represent a better use of public funds than the continued subsidization of conventional insurance.

The Mexican and Kenyan cases also highlight the savings afforded to the public budget by the implemented index insurance programs; in the case of Mexico by reducing direct support and disaster relief payments in the wake of catastrophic weather events and in the case of Kenya by reduced alliance on international funds for food aid.

The portrayed cases also suggest that index insurance is both a dynamic field and a field that has significant scope for improvement moving forward. Contract design can be improved and basis risk reduced by using new data sources that permit alternative indices or by more effective use of existing data (following, for example, the observations of Fuchs and Wolff (2011b) for Mexico's catastrophic weather index insurance). Creative use of satellite imagery (as in the case of the IBLI contract in Kenya) has recently allowed governments and the private sector to extend insurance coverage to previously uninsurable areas. The big data revolution (i.e., the availability of higher quality data and more developed computing power and methods for analysis) is likely to significantly increase the dynamism of the index insurance sector by further expanding the types of data that can be used to design indices and extending geographic coverage. The challenges implicit in the successful utilization of big data in developing countries, however, suggest that the development of public-private partnerships will be crucial in order to take advantage of the potential offered by big data.

All indices require reliable and long series of data. However, the absence of data need not prevent the development and implementation of index insurance initiatives. Strategies such as public-private partnerships for insurance or reinsurance, and hybrid combinations of multiple indices as well as indices combined with on-farm yield audits should be considered. Instead of a vicious cycle that discourages the development of index insurance, innovative efforts such as those discussed here to overcome data limitations can create a virtuous cycle in which the productive use of information, (i.e. the development of index insurance schemes), encourages further public (and also private) investment to improve the timing, quantity and quality of data collection. This virtuous cycle can lead to the creation and expansion of a sustainable insurance market that can effectively add value to farm businesses, lending institutions and other service providers along the agricultural supply chain.

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