Suitability of index insurance: new insights from satellite data

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Abstract

Index insurance has been promoted as a promising solution for reducing agricultural risk compared to traditional indemnity-based insurance. By linking payouts to an external variable instead of individual loss, index insurance reduces monitoring costs, and alleviates the problems of moral hazard and adverse selection. Despite its theoretical appeal, demand for index insurance has remained unexpectedly low in many developing countries, triggering a debate on the causes of the low uptake. Surprisingly, there has been little discussion in this debate about the US experience, although it is a unique case where both indemnity-based insurance and index insurance have been available for more than two decades. In this case too however, actual take-up of index insurance is very low, never more than 5% of insured acreage. Does this mean that we should give up on index insurance?

In this paper, we investigate the low take-up of area-based insurance using a field-level dataset for corn and soybeans obtained from satellite predictions. While previous studies were either based on county means or used relatively small farm-level dataset, our satellite-derived data gives us a very large number of fields (close to 1,800,000) comprised within a large number of index zones (600) observed over 20 years. To abstract from moral hazard and adverse selection, we run a simulation experiment, comparing the benefits of both insurance plans using a new measure of farm-equivalent risk coverage of index insurance. Results indicate that the simulated risk coverage of index insurance is higher than previously thought, suggesting a higher theoretical take-up than observed in practice. Our results reveal however an interesting paradox, where counties with the highest temporal variability have also the highest spatial variability. This implies that counties where insurance is the most needed are also the ones where index insurance is the least effective. Based on this, we investigate how satellite data can help us design optimal insurances areas, instead of relying on arbitrary county boundaries.

1 Introduction

Risk is ubiquitous in agriculture. Weather has an important influence on production, yet remains difficult to predict. Likewise, agricultural prices are typically very volatile, as experienced for example during the price spike in 2007-2008. This risk has several negative consequences on farmers. In presence of risk, farmers reduce output, and opt for low-yielding low-risk technologies. Further, in developing countries with missing credit markets, risk affects negatively farmer's ability to smooth consumption, and reduces both demand and supply of credit (Boucher et al., 2008; Karlan et al., 2014).

Agricultural insurance is an important tool to reduce the risk faced by farmers. Historically, initial insurance instruments focused on indemnity-based schemes, where payouts are triggered when yields on a given field fall below a certain percentage of the field's expected yield. This *field-based* scheme suffers however from multiple issues: 1) moral hazard, where being insured leads to taking undue risk, 2) adverse selection, where the possible under and over-evaluation of individual risk leads to adverse sorting of farmers, and finally 3) high monitoring costs due to the requirement of assessing damage and the data needed for pricing individual premiums. As a response to these issues, index insurance offers an interesting alternative. Index insurance links the insurance payout to low realizations of an external index, which is often defined based on output (average yields in a given area) or inputs (weather variables such as rainfall, temperature, etc). The advantages of index insurance are reduced costs as monitoring individual fields is no longer necessary, absence of moral hazard since farmers individual actions have no influence on the index, and potentially reduced adverse selection.[1] These advantages of index insurance over traditional indemnity-based insurance have led to the implementation of several schemes throughout the world, in particular in developing countries, and to a sustained interest in the literature (see the reviews by Barnett and Mahul, 2007; Miranda and Farrin, 2012; Carter et al., 2017).

Despite of the theoretical appeal of index insurance, success of the various schemes implemented is rather limited, as summarized by Binswanger-Mkhize (2012) paper title, *Is There Too Much Hype about Index-based Agricultural Insurance?* In general, take-up is found to be very low, even at subsidized premium rates, questioning the sustainability of such schemes without public or donor support. The main culprit lies in the principle itself of index insurance: by de-linking payouts from individual losses, index insurance introduces *basis risk*, i.e. the probability that a farmer experiences a loss whereas the index does not lead to a payout. Ultimately, basis risk is a function of the index accuracy, and hence depends on whether aggregate yields (for outcome-based indices) or specific rainfall variables (for input-based indices) predict well individual yields. While basis risk is widely acknowledged as the main issue of index insurance, few studies have however been able to measure it in practice. Among

[1]Note that adverse selection due to spatial or temporal variations in the accuracy of the index is still possible, see Jensen et al. (2018).

the few of those, Jensen et al. (2016) analyze a livestock index insurance program in Kenya using four years of data, and conclude with a cautionary note, finding a substantial basis risk.

In this paper, we take advantage of satellite data techniques to construct a large dataset of field-level yields for corn and soybeans in the Corn Belt area of the United States of America. This enables us to conduct an in-depth analysis of basis risk, and compare the suitability of index insurance over a large number of zones. The US Corn Belt offers an interesting case to study for two main reasons. Firstly, its large and rather uniform fields offer a particularly favorable setting for satellite data, and accuracy of the satellite predictions is currently higher than in many other countries. Second, the US hosts one of the largest and possibly oldest index insurance scheme, based on county average yields. Interestingly, and somehow underappreciated in the literature, lessons from this scheme are not very encouraging as take-up is very low compared to demand for the traditional indemnity-based schemes also offered in the US. Obviously, many explanations for this low take-up of index insurance pertain to peculiarities of the US context, yet we believe that the lessons from the US case have a larger relevance in the global discussion on index insurance. In particular, the US case provides probably an upper-bound for the suitability of index insurance in general, as its relatively homogeneous production system makes it well-suited for an output-based index insurance. We would expect basis risk to be higher in developing settings characterized by larger heterogeneitydue to disparities in access to technology, information and credit.

Using satellite data provides us with a very rich dataset compared to any other study. Our dataset contains the majority of fields in each of the close to 600 counties in nine states within the US Corn Belt.[2] We observe corn and soybeans yields over a fairly long period of 20 years (2000-2019), which is long enough to comprise normal cropping years as well as exceptional events such as the 2012 drought. Keeping only fields for which we have a high classification accuracy as well as at least eight years planted to corn or soybeans, we end up with 1.8 million fields, representing 2.8 M field-crop pairs. Previous studies in the US used much shorter dataset, ranging from a few hundred fields in Miranda (1991), Smith et al. (1994), Carriker et al. (1991) to above one thousand fields in Deng et al. (2007). Barnett et al. (2005) have to our knowledge the largest number of fields in the literature -60'000 corn producers- yet these are spread out over ten states and contain hence only few fields per county, making it difficult to conduct a comprehensive basis risk analysis. In developing countries, dataset are even smaller, and contain typically one to two thousand households, covering shorter time periods given the later implementation of index insurance schemes (Jensen et al., 2016; Flatnes et al., 2018).

To analyze the suitability of index insurance, we proceed in two steps. We first run an analysis at the individual level, comparing for every field the expected utility of 1) no insurance, 2) field-level insurance and 3) index insurance.

[2]The states are Iowa, Indiana, Illinois, Ohio, Michigan, Minnesota, Missouri, South Dakota and Wisconsin.

In a second step, we aggregate these measures at the county level, and using Miranda (1991)'s framework, we compute county-level measures of basis risk. We compare these various county-level metrics of index insurance suitability to county characteristics such as temporal and spatial variance, seeking to predict which counties are the most suited for index insurance. Later on, we take advantage of the spatially-explicit nature of our data to investigate whether we can redesign zones in a more natural way instead of relying on arbitrary administrative boundaries.

Our whole analysis is based on a simplified insurance scheme, where we compute ex-post fair premiums and compute the benefits of insurance assuming the farmer takes the product every single year. By doing so, we rule out moral hazard and adverse selection, and abstract from the real-world intricacies of the Federal Crop Insurance system. We do not seek either to factor in the differences in costs between the different schemes, which are hard to measure in practice. These abstractions are useful as they allow us to focus on the core question, that of basis risk and suitability of index insurance per se. This also alleviates the need to make strong assumptions and settle for specific models of moral hazard or adverse selection. Taken all together, we are probably underestimating the benefits of index insurance from the insurer perspective, as we are not modeling the benefits of lower monitoring costs and absence of moral hazard.

The paper is organized as follows: in Section 2, we describe the Federal Crop Insurance Program, and present our modeling approach. Section 3 presents the dataset, its construction and validation. Finally, in Section 4, we show our main results.

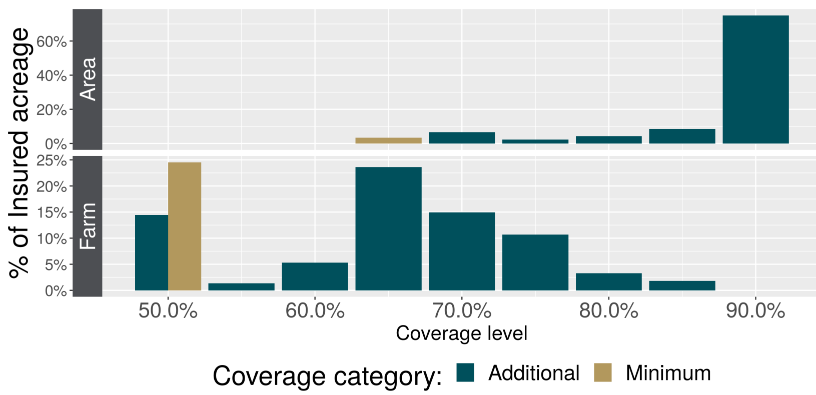
2 Context and conceptual model

2.1 The US Federal Crop Insurance Program

The US Federal crop insurance program has become since its inception in 1938 one of the largest programs of the Farm Bill, costing close to $8 billions a year, second only to the nutrition program. These large costs can be explained by the generous nature of the program: the government covers all operational costs, and subsidizes a large share of the premiums (60% on average). These high subsidy rates are deemed necessary to induce farmers to participate into the program, given the relatively low initial participation rates in early years. Participation is now high, with about 86% of eligible acres covered in 2015.

The Risk Management Agency (RMA) has offered a plethora of insurance plans throughout the years, with evolving names and specificities. In a nutshell, these can be classified into plans insuring yields or revenue, and into plans insuring at the farm-level or at the county-level. Yield insurance at the farm level was historically the standard insurance plan. Area-based plans were introduced in 1993 under the initial name of Group Risk Plan. This area-based plan is an index scheme, where the index is the average county yield

Figure 1: Demand for insurance at various trigger levels



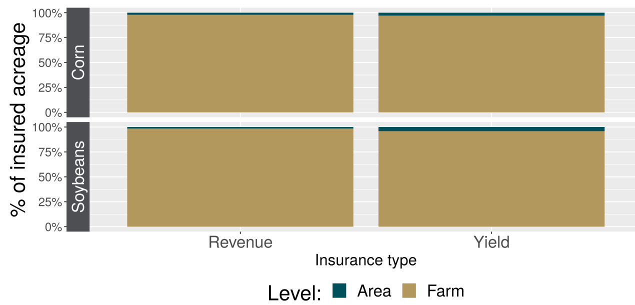
Source: Own computation from Risk Management Agency's Summary of Business

as measured by official statistics collected by the US Department of Agriculture (USDA). The general idea behind all these plans is that indemnities are triggered whenever actual (farm or area) yield is below a certain percentage of its expected value. This *trigger* level (called somehow ambiguously coverage level in RMA termsis offered at various levels, ranging from 50% to 85% for farm-level, and 65% to 90% for the area-based product. Premiums are heavily subsidized, at an average rate of 60%, with the rate decreasing for higher levels of trigger (see Table 1). Figure 1 shows the trigger levels selected by the farmers for the farm- and area-based insurance over the 2011-2019 period averaging over corn and soybeans. The figure shows also the so-called catastrophic trigger (CAT) which comes at lower cost yet delivers lower indemnity. Strong differences appear between the farm and area-yield trigger selected. For the area-based scheme, the vast majority chooses the maximum trigger level, 90%. On the other side, for the farm-based product, farmers choose either the lowest trigger at 50%, or an intermediate value of 65%, while very few opt for the maximum coverage at 85%.[3] This difference between the trigger choice for farm- or area-based coverage suggests that area-based provides only a partial protection due to the basis risk.

Do farmers prefer area- or farm-based insurance? Figure 2 shows the percentage of each scheme in terms of total acreage covered, both for the yield and revenue types. The demand for index insurance is very small, not more than 5% in each case compared to traditional indemnity-based insurance. These results do not appear very encouraging for index insurance, casting doubt as to whether index insurance should be promoted at all. One should bare in mind however that it is difficult to compare directly the two products. Not only are subsidy rates different, but there are plenty subtle differences that we

[3]The fact that farmers select only intermediate coverage for the farm-value has been discussed in various papers, see Du et al. (2016); Babcock (2015); Feng et al. (2020)

Figure 2: Demand for area versus farm-based insurance



Source: Own computation from Risk Management Agency's Summary of Business

sidestepped for the sake of clarity.[4] Interestingly, a similar product with both a farm- and area-based option is offered by the USDA Farm Service Agency, and there the conclusion is reversed: the area-based product is largely preferred over the farm-based one (Schnitkey et al., 2015). This observation motivates our approach below to evaluating the benefits of index insurance using a stylized representation abstracting from many institutional peculiarities.

2.2 Conceptual model

We follow here the model of Miranda (1991) measuring the benefit of area-based index insurance. We write y_{ict} as the yield for field i in county c at time t, and write the annual county average yield as $\bar{y}_{\cdot ct}$, the long-term county average yield as $\bar{\bar{y}}_{\cdot c \cdot}$, where the $\cdot$ notation indicates over which dimension the averaging is done.[5] The county-level payout is triggered whenever actual county yields $\bar{y}_{\cdot ct}$ are below their long term target $\tau_i \bar{\bar{y}}_{\cdot c \cdot}$, where τ_i is the trigger level chosen by farmer i. Miranda considers a simplified payout scheme,[6] where the indemnity is the difference between target county yields and actual county yields whenever actual county yields are below, i.e. $I^c_{ct} = \max(\tau_i \bar{\bar{y}}_{\cdot c \cdot} - \bar{y}_{\cdot ct}, 0)$. Note that for ease of exposition the indemnity is expressed in yields units, not scaled to dollars units, which are here unnecessary given that our focus is on yield, not revenue insurance. Turning to the farm-based insurance, we consider later on the same indemnity scheme, simply replacing county yields by individual field yields: $I^F_{ict} = \max(\bar{y}_{ic\cdot} \tau_i - y_{ict}, 0)$, where $\bar{y}_{ic\cdot}$ is the field-level mean. Miranda's

[4]Most notably, we did not discuss here the details related to the *protection price* for area-based insurance, nor the *enterprise units* for farm-based insurance, all with different subsidy rates. Likewise, *yield exclusion* options allowing to exclude a particularly bad year from the farm-level premiums increase the attractivity of farm-level products.

[5]As an example, $\bar{y}_{\cdot ct} \equiv 1/n_{i^c} \sum_{i \in c} y_{ict}$ denotes the county mean over time.

[6]The actual indemnity scheme divides the difference by the trigger τ_i, and contains also a *protection factor*, which allows to scale up or down the indemnity payment. The RMA does to our knowledge not provide data on insurance take-up by protection factor level, so we simply set it to 100%, to ease comparison with farm-level insurance. See Skees et al. (1997) for details.

model is based on β_{ic}, the coefficient of a regression over time of individual yields y_{ict} against county yields $\bar{y}_{\cdot ct}$:

$$y_{ict} = \alpha_{ic} + \beta_{ic}\bar{y}_{\cdot ct} + \epsilon_{ict} \tag{1}$$

Intuitively, β_{ic} indicates how well a farmer's yield is correlated to the county yield. The term ϵ_{ict} represents idiosyncratic farmer-specific shocks, that cannot be insured by a county-level insurance scheme. Miranda analyses the benefits of area-based insurance using a mean-variance framework. When premiums are fair, the absolute difference in mean-variance utility between area-based and no insurance amounts to the difference in variance. Miranda shows that this variance reduction Δ_{ic} is a function of the farmer's own β_{ic} and a county-level *critical beta* value $\tilde{\beta}_c$: $\Delta_{ic} = \sigma^2_{IC}[\beta_{ic}/\tilde{\beta}_c - 1]$, where σ^2_{IC} is the variance of the indemnity. The risk is reduced for all farmers above the critical beta, i.e. $\beta_{ic} > \tilde{\beta}_c$. Further theoretical refinements of Miranda's model focusing on the design of an optimal contract were made by Mahul (1999), Vercammen (2000) and Bourgeon and Chambers (2003).

The use of a mean-variance utility function is however somehow controversial. Jensen et al. (2016) argue in particular that the assumption of symmetry in preference between positive and negative shocks is not very relevant for the context of crop insurance, targeted at reducing negative shocks. Using a general expected utility framework is more theoretically coherent, yet unfortunately does not lead to simple analytical expressions. We can however use a second-order Taylor approximation and still obtain analytical results. The absolute difference in utility Δu_{ic} becomes now: $\Delta \operatorname{E}[u_{ic}] \approx -1/2u''(\mu_{ic})\Delta_{ic}$, where μ_{ic} is the expected value of the field-level mean $\bar{y}_{ic\cdot}$ and Δ_{ic} Miranda's variance reduction factor. Importantly, Miranda's result that only farmers with $\beta_{ic} > \tilde{\beta}_c$ will benefit from index insurance still holds. Given the difficulty of obtaining analytical results in the general case, we will proceed below to a simple empirical evaluation of utility of the various insurance plans based on (simulated) yield data. Instead of expressing our comparison in utility units, we use certainty equivalents (CE), which are expressed in yield metrics. The certainty equivalent is the non-random value whose utility is the same as the expected utility from a random *lottery*, where the lottery here is simply the set of observed yields. That is, CE is the value such that $u(CE) = E[U(y)]$ holds. A higher CE is equivalent to a higher utility, and hence we simply compare index insurance versus no insurance based on their ratio CE^I/CE^{no}. A ratio >1 implies a higher utility of index insurance, $U^I > U^{no}$.

As discussed in the beginning, basis risk is often considered the main issue with index insurance. Basis risk is often defined as the risk that the farmer experiences a loss, while the index does not leads to a payout. The reverse situation of the farmer experiencing no loss yet receiving an indemnity is also possible, but usually not taken into account, as the emphasis is on the ability of an insurance scheme to reduce negative events, not to amplify positive ones.[7]

[7] It should be noted however that insurance windfalls have also an indirect negative impact by increasing premiums.

Following Elabed et al. (2013) we can consider the *False Negative Probability FNP*:

$$FNP(\theta_c, \theta_i) \equiv P(\bar{y}_{\cdot ct} > \theta_c | y_{ict} < \theta_i)$$

Here θ_c is a county loss threshold, and θ_i is a farmer-specific subjective loss threshold. This measure is however unsatisfying for multiple reasons. First of all, it requires to define specific loss thresholds θ_c and θ_i, which is mostly arbitrary given that yields are a continuous variable. Second, this is only a probability between 0 and 1, and hence is not indicative of the amount of loss experienced. An insurance missing a particularly catastrophic event yet delivering payouts for all other small loss events would be deemed to offer a low basis risk despite not serving when it is the most needed.[8] We adopt here another definition of basis risk, related to the county yield regression (1). We look at the variance of residuals σ_ϵ^2 normalized by the field-specific variance, that is $1 - R_{ic}^2$. This represents the amount of idiosyncratic risk that can not be insured by the index. A value of 0 indicates perfect correlation with the index, while a value of 1 indicates that the variables are fully uncorrelated. In the latter case, $\beta_{ic} \rightarrow 0$ so that the reduction in variance Δ_{ic} is negative, indicating that the area insurance provides less utility than without insurance.[9]

The discussion so far focused on measuring the benefits of index insurance versus no insurance. The next question to raise is how index insurance compares to farm-based insurance, which is a more stringent and also more informative test. Noting that no-insurance is equivalent to a farm-based insurance with a 0% trigger level, we seek to strengthen our comparison, comparing now the utility of index insurance versus increasing levels of farm-based insurance. We name such measure the *farm-equivalent risk coverage*, which we define as the highest level of farm-based insurance for which index insurance is at least as good or better. The higher this number is, the more protection index insurance gives in terms of an ideal farm-based scheme. Formally, our measure is defined as:

$$\tau^* \equiv \max_{\tau \in \{0.2, \ldots, 0.9\}} \tau \quad \text{such that} \quad U_{90\%}^{area} > U_{\tau\%}^{farm}$$

We set the value of 90% for the area insurance as this is the value most selected by farmers, and search over a large set candidates values of $\{0.2, \ldots, 0.85, 0.9\}$ which includes all values offered by the RMA (from 0.5 to 0.85). For an index-insurance with a trigger of 90%, this measure will typically lie in the interval $[0\%, 90\%]$. The upper bound comes from the fact that at equal trigger level, a farm-based insurance is superior, as it covers also the idiosyncratic risk on top of the systematic covered by the index insurance. We still include the value of

[8]See Clarke (see 2016); Barré et al. (see 2016) for an in-depth discussion of metrics for index insurance.

[9]This is true for a mean-variance utility function, as well as for any utility function up to a second-order approximation.

90%, as in some cases, the index at 90% turns out be to better than the farm-level insurance at 90% due to random chance.

A limitation of our measure is that it remains undefined in two cases. For one, if index insurance is not even as good as no insurance, then it is clear that it won't be better than any level of farm-based insurance. In this case, we attribute a τ value of 0%. The second limitation arises from the fact that we can only observe the utility of farm-level insurance for those trigger levels at which there is a yield fallout happening. If for a given field the minimum yield observed is say at 70% of the average yield, then farm plans covering 50% to 65% will not provide any protection, and hence will give the same utility as the situation without insurance. If however index insurance is inferior to the minimum observed relative yield, we only know that it lies in an interval $[0, y_{\min}/\bar{y}[$. These two limitations raise issues for the aggregation of our *farm-equivalent risk coverage* at the county level. To address these two issues, we consider rank statistics such as the median and the proportion of fields within a county which have $\tau_i > 0.85$, as well as $\tau_i > 0.50$.[10] These numbers correspond to the highest and lowest levels of farm protection available. The 50% level is also called *catastrophic* protection, so serves as a good benchmark for the minimum protection level index insurance should provide. The 85% level on the other side corresponds to the best possible farm-level protection, so any field with a farm-equivalent risk coverage at 85% or above would strictly prefer area-based insurance over far-based insurance.

To measure the direct benefit of index insurance both versus no insurance and versus farm-insurance, we simply specify a-priori the same utility function for all fields, and evaluate our measures based on the yields with or without insurance. Following previous literature (Wang et al., 1998; Deng et al., 2008; Flatnes et al., 2018) we use a constant relative risk aversion (CRRA) iso-elastic utility function, with a parameter of 1.5. Fair premiums and indemnities are computed ex-post from the data. By following this procedure, we make two fundamental assumptions. Firstly, we are assuming that yields are the same whether or not the farmer takes insurance. This means that we are ruling out possible moral hazard. Second, we are computing ex-post fair premiums assuming the farmer takes the insurance every period, ruling out adverse selection. While this makes us depart from real-world characteristics in an important way, this allows us to focus on our main topic of interest, the utility of index insurance.

A defining characteristic of production in the Corn Belt is the practice of rotation between corn and soybeans (see Hennessy, 2006; Seifert et al., 2017). Given the large dataset we have, we observe almost every possible sequences of corn and soybean (and other crops), from always corn, always soy, always rotating to any other intermediate combinations. This raises a problem for the computation of fair premiums. Our fair premiums are computed using county

[10] Using rank statistics will take care of the issue of aggregating over zero values. It will also partially address the problem of undefined values, although there is still a small percentage of fields with relative minimum above 85% (or above 55%) which would be miscounted. The total percentage of undefined values is however relatively small, between 2% and 5%.

yields for the whole period. This means that the premiums will be fair for fields planting always corn (or always soy) over the whole period. But for other fields, the premium might be exceptionally favorable (say field is planted to corn only in drought year 2012 and receive huge indemnity) or very unfavorable (field is planted to corn every year but 2012). This brings important randomness in our data, making our comparisons blurred. To avoid this, we decide to simulate yields, providing us with a sample of corn and soy yields every year for each field. This has three further advantages. First of all, this allows us to extend the time length of our sample, which we simulate using NASS means from 1990 to 2018. Second, having more observations for each field increases the probability of observing lower minimum values for each field, attenuating the problem of undefinedness of our farm-equivalent measure, which is not defined if the observed relative minimum is too high. Finally, simulating data can be seen as a measurement error correction, where we adjust our sample to match official county means. Yield is simulated based on the field-to-county regression (1): for each farmer we estimate $\hat{\alpha}_{ic}$, $\hat{\beta}_{ic}$ and $\hat{\sigma}^2_{ic}$. We then plug-in detrended NASS county means $\tilde{y}^{NASS}_{ct}$ from 1990 to 2018, and simulate residuals from a $\mathcal{N}(0, \hat{\sigma}^2_{ic})$, that is $\hat{y}_{ict} \sim \mathcal{N}(\hat{\alpha}_{ic} + \hat{\beta}_{ic}\tilde{y}^{NASS}_{ct}, \hat{\sigma}^2_{ic})$. To avoid simulating outlying observations, we actually simulate using a truncated normal distribution, setting generous lower bounds of 10 [bu/acres] for both crops, and upper bounds of 100 [bu/acres] for soy and 350 [bu/acres] for corn.

3 Data

The yield data comes from the SCYM model developed by Lobell et al. (2015); Jin et al. (2017); Deines et al. (2019a); Dado et al. (2019). The method predict yields based on a satellite-derived vegetation index.[11] Parameters linking the satellite-observed vegetation index to predicted yields are derived from an agronomic crop growth model. In brief, the agronomic model is used to simulate multiple realizations of *pseudo* yields and vegetation values. These simulated pseudo values are used to estimate a regression between vegetation index and yields. These estimated parameters are used in turn to predict yield based this time on the satellite-observed vegetation index. The advantage of this method is that it does not make use of ground data for calibration purpose. When ground truth data is available, it can be used as true out-of-sample validation. When validated against ground truth data for more than twenty thousand corn fields, Deines et al. (2019a) find that the overall correlation for corn is 0.67 at the field level, and increases to 0.85 when computed against NASS county means. Accuracy for soybeans is typically lower. Different versions of this dataset have been already used in various studies, Lobell and Azzari (2017) look at increasing field heterogeneity over time, Seifert et al. (2018)

[11]The methods uses the so-called Green Chlorophyll Vegetation index (GCVI) which is similar in spirit to the widely known normalized difference index, NDVI.

study the effect of cover crops, Deines et al. (2019b) study the effect of conservation tillage, Stigler (2019) estimates the effect of rotation and Stigler (2018) measures the supply response to prices. We use here an updated version of the dataset drawing on the developments by Deines et al. (2019a); Dado et al. (2019). Previous versions of the dataset were predicting yields for those pixels designated as corn and soybeans by the Cropland Data Layer (CDL) from Boryan et al. (2011). This crop map covers nine states of interest in the Corn Belt, yet starts at different periods depending on the state, with starting dates ranging from 2000 to 2008. To have a consistent sample, we use for 2000-2007 the crop map of Wang et al. (2020), who use random forests to expands the CDL from 2000 onwards for the nine states we consider here.

The SCYM dataset is at the pixel level, which is not very relevant to our analysis here. We use a dataset of field boundaries, the Common Land Unit (CLU). This dataset was last available for the year 2008, so field shapes might have changed in the meanwhile. To address this, we select only fields for which there is a good classification agreement throughout the years. That is, we compute the frequency of the majority vote from the Cropland Data Layer (CDL) pixel classification, and retain only fields that have on average 85% of classification agreement. Put differently, we require that for a given field, the CDL consistently predicts either corn or soybean for 85% of the pixels throughout the years. The pixel count is done by only considering pixels within a negative 30m buffer, avoiding contamination by mixed pixels lying on the border of the field. Averaging of the SCYM yields within the field boundary is made using the same subset of interior pixels.

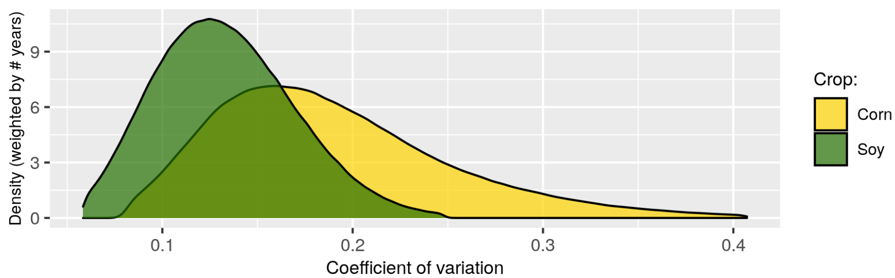
We apply two filters on the initial set of available field boundaries. Besides filter field boundaries to keep only those well classified, we also restrict the sample ti consider field-crop pairs that have at least eight years of observations in corn or soybeans. This is to guarantee statistical accuracy when we estimate the field-to-county regressions. This implies that we might observe a field for only one crop or for both. Applying these two filters, we are left with 1.8 million fields in the 9 states we consider. Among these 1.8 millions fields, for 54% of those we observe data on both crops (i.e. we have more than ≥ 8 observations for both corn and soybeans), while for 28% we observe only corn and 18% only for soy, which gives us 2.8 million field-crop pairs. The sample runs from 2000 to 2019, and the total size of our sample is ~ 30 million field-crop-year observations.

4 Results

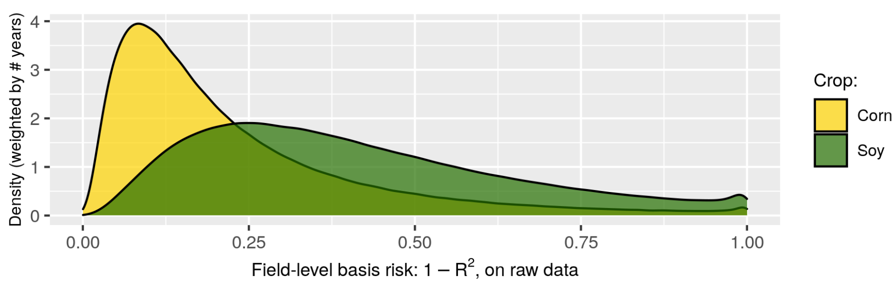
To start with, we compare the field-level variability over time of corn and soybean. Figure 3a shows first the field-level time variance (expressed as coefficient of variation for ease of comparison) and 3b its idiosyncratic part, as measured by the $1 - R^2$ from the field-to-county regression. Interestingly, while corn appears more variable than soybean, its variability is better captured by co-movement with county averages, so that the idiosyncratic variability is much

Figure 3: Field level total and idiosyncratic variability (raw data)

(a) Coefficient of variation



(b) Basis risk $1 - R^2$

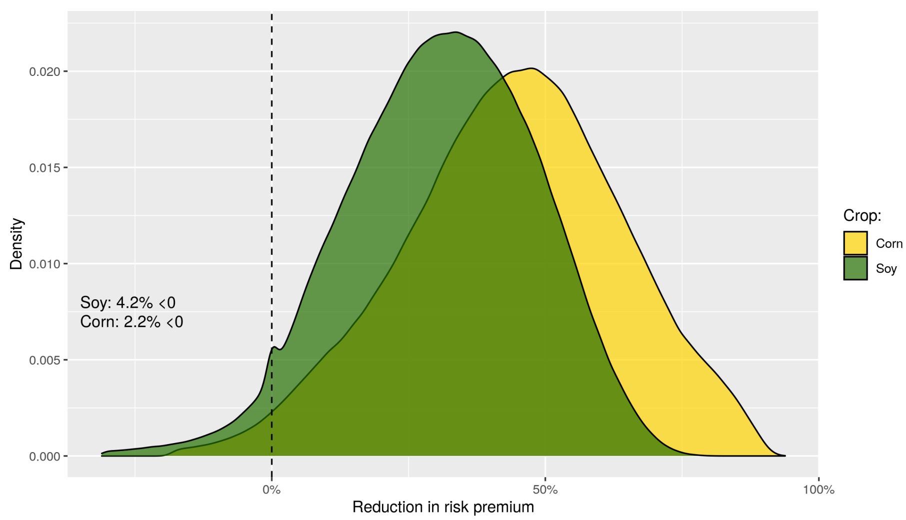


Source: Own computation from SCYM. We kept only fields that have at least 8 observation for each crop. The density is further computed by weighting fields by the number of years available.

lower than for soybeans. In our simulated sample, average corn yields over fields and years is 162 [bu/acre], and 51.7 for soy. Given the risk-aversion function we specified, this amounts to a certainty equivalent (CE) of 155 [bu/acre] for corn and 51 [bu/acre] for soy. The difference between the average and CE, called the *risk premium*, indicates the cost of risk. Here, risk induces a welfare loss in yield metric of 7 [bu/acre] for corn and 0.6 for soy, amounting to 4.3% and 1.2% in percentage.

We turn now to our two main measures of the utility of index insurance, the utility of index insurance versus no insurance, and the *farm-equivalent risk coverage*. Figure 4 shows the density of the risk premium reduction. This indicates how the risk premium of no insurance is reduced with index insurance, a higher reduction meaning higher utility from index insurance. We see clearly that index insurance provides more risk reduction compared to soybeans. The average reduction for corn is 43%, while that for soybeans is about 30%. The proportion of fields for which the reduction is negative, i.e. utility from index insurance is actually lower than without insurance, is also lower for corn, at 2.2% against 4.2% for soybeans. The better results for corn seems to be in line

Figure 4: Comparing index insurance versus none: reduction in risk premium

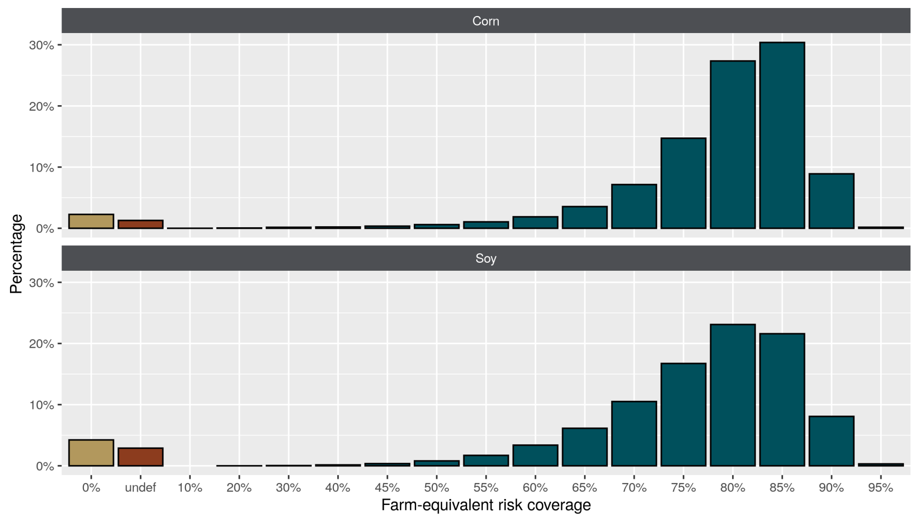


with the findings from Figure 3b, which showed that the basis risk was lower for corn.

Moving to the more stringent comparison between index insurance and farm insurance, Figure 5 shows our measure of *farm-equivalent risk coverage*. The category 0% indicates fields for which index insurance is not even as good as no insurance. These are the same percentage as the ones in Figure 4. The category *undef* corresponds to those fields for which our measure is undefined due to the fact that the utility of index insurance is lower than the smallest observed farm-equivalent category, yet higher than no insurance. Focusing on the subset of well-defined values, it is apparent again that corn provides a higher protection than soybeans. Looking at our measure of fields with at least an equivalent coverage of 85%, this number is relatively high, at 40% and 30% percent respectively. This is an important result, as it suggests that index insurance performs quite well relatively to the best available farm-level insurance level. Another interesting level to compare to is the 50% trigger, which is also the so-called *catastrophic* level offered at very low cost for farm-level insurance. There is now a large amount of fields for which index insurance is at least as good as this 50% level, 95% for corn and 92% for soybeans.[12] Note that the 90% and 95% triggers are not offered by the RMA at the farm level, and we would expect that index insurance at 90% does not perform better than farm-level insurance at the same 90% trigger or even higher 95%. Computing the *farm-equivalent risk coverage* for the 90% trigger is however informative on the randomness of our simulation: had we simulated data for a longer period

[12]This number is possibly under-estimated due to the *undef* category, which corresponds to fields whose farm-equivalent coverage is identifiable only over an interval. Likely, some of these fields would have a value above 50%, yet are not counted as $<$ 50% in this statistic.

Figure 5: Comparing index insurance versus farm insurance



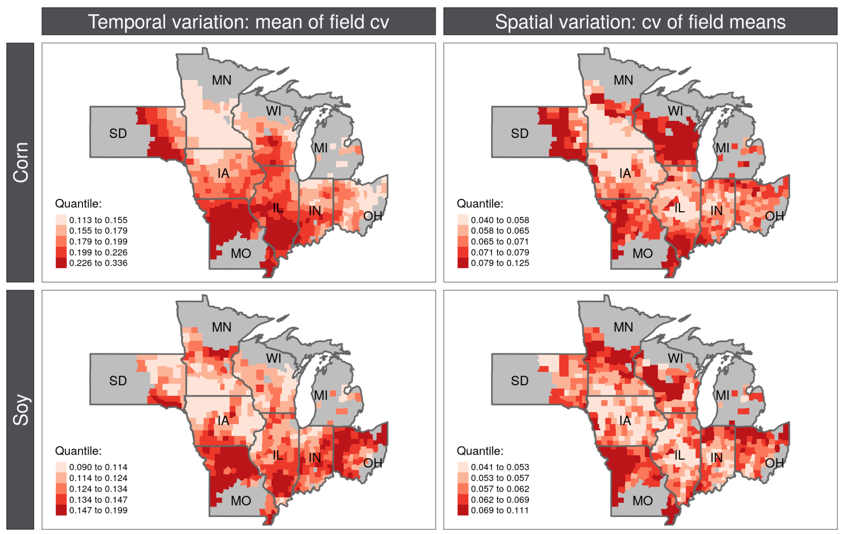
than 30 years, fields with index insurance better than the 90% farm-level trigger would certainly shrink rapidly.

Concluding this first section, we find evidence in favor of index insurance, although the metric we consider play an important role. When doing a raw comparison versus no insurance at all, we find that a high number of fields, 98% of corn and 95% of soy fields, would benefit from index insurance. When comparing against the more stringent criterion of farm-equivalent risk coverage, we find again that for a relatively large number of fields, index insurance compares at least as well as the minimum catastrophic rate of 50% (95% and 72% for corn and soy). Finally, when subjected to the highest criterion comparing it to the maximum available farm-level trigger level of 85%, a smaller yet still large proportion of fields would still prefer index insurance, at 40% and 30%. Interestingly, this number is still much higher than the observed take-up of index insurance (see Figure 1).

We proceed now to a cross-county comparison of the suitability of index insurance, relating our measures of index insurance utility to characteristics of the 597 counties in our dataset. We start by showing the spatial and temporal variation of yields between counties. The county-average *temporal variability* is computed as the mean of every field's temporal variance.[13] The county average *spatial variability* is computed as the variance of the field means. It basically indicates how different are fields within a county, and is related to the concept of local yield gap. Figure 6 shows these measures for each crop. The two

[13]Note that this county average of field-level temporal variance $\overline{\sigma_i^2}$ is related yet distinct from the variance of the county average, $\text{Var}(\bar{y}_{\cdot t}) = 1/N\overline{\sigma_i^2} + (N-1)/N\bar{\rho}$, where $\bar{\rho}$ is the average correlation among fields.

Figure 6: Corn: temporal and spatial variability



measures show clear spatial patterns with a *core versus periphery* pattern, where variability is relatively low in the center of the Corn Belt, in particular in Iowa (IA), North of Illinois (IL) and South of Minnesota (MN). On the other side, bordering regions such as South Dakota (SD), Missouri, and South of Illinois (IL), Indiana (IN), Ohio, Michigan (MI) and Wisconsin (WI), have markedly higher variability. This spatial pattern is similar across crops or variables, with a correlation between variables of 0.43 for corn and 0.36 for soy, while for the same variability measure, the correlation between corn and soy is 0.5 for the temporal variation, and 0.55 for the spatial variation.

Turning now to the insurance utility measures based on the simulated data, Figure 7 compares index insurance versus none by showing the percentage difference in certainty equivalent (CE) of index insurance compared to no insurance. Interestingly, the benefit of index insurance is high in the *periphery* regions that have a high variability. It is indeed particularly high in Missouri (MO) and southern Illinois (IL), which are regions with both high temporal and spatial variability. In contrast, index insurance seems to be of more limited use in the *core* regions such as northern Iowa (IA) and southern Minnesota. Figure 8 compares on the other side the index insurance to the farm-based insurance, using our measure of *farm-equivalent risk coverage* at 85%. The conclusion is now reversed: counties in the *periphery* have a low farm-equivalent risk coverage, while those in the *core* show much higher benefits from index insurance. Most counties in Iowa (IA) have 40% or more of their fields which would strictly benefit from index insurance even compare to farm-based protection at 85%.

The previous results reveal an interesting reversal: counties where index

Figure 7: Utility comparison: area-plan versus no insurance

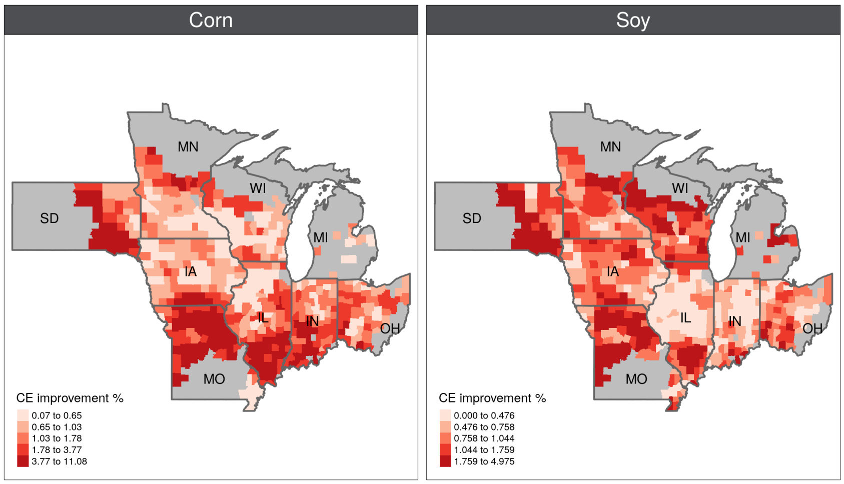


Figure 8: Farm-coverage equivalent of area insurance: percentage of fields within county with coverage > 85%

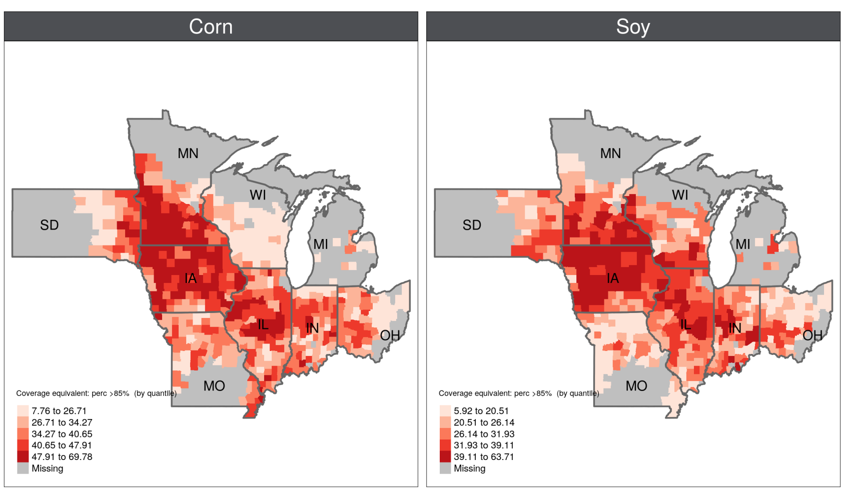
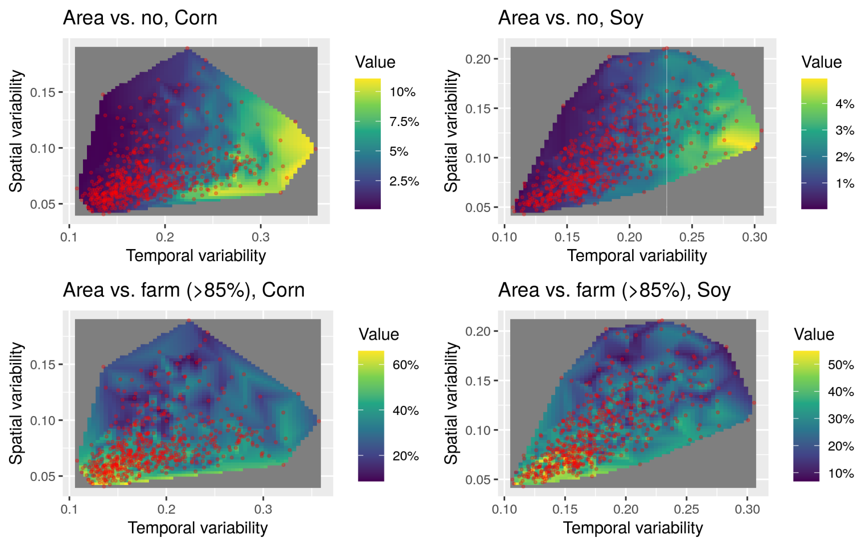


Figure 9: Utility of insurance according to county temporal and spatial variability



insurance appears to be the most useful when assessed against no insurance turn out to be counties in which index insurance is the least beneficial in term of farm-equivalent protection. This paradox stems from the fact that temporal and spatial variability happen to be positively correlated, yet these have opposite effects on the usefulness of index insurance. To make this point clearer, Figure 9 show the value of index insurance (compared to no insurance or to farm insurance), projected in the spatial-temporal variability space. The index insurance utility metrics were interpolated, and red dots indicate the actual value of the near 600 counties in our sample. The first row shows the values for the utility of index insurance versus no insurance. Highest utility is found on the east side of the space, where temporal variability is highest. The gradient of utility along the temporal variability (x-axis) is so strong that it appears to obscure the effect of spatial variability (y axis), which seems to have almost no impact on the utility of index insurance. However, when looking at the utility of index insurance compared to farm insurance on the second row, results are reversed, much as we saw from maps 7 and 8. The highest utility of index insurance is now on the south-west part of the graph, where spatial and temporal variability are lowest. The east portion that was previously giving the highest utility when compared to no insurance gives now almost the lowest utility.

The reversal we document here leads to a puzzling paradox: those places where risk is highest and hence where insurance is the most needed are also those where index insurance is the least useful. Said differently, index insurance leads to good farm-equivalent coverage only in those counties that have the lowest risk. Because of the positive correlation between temporal and spatial variability, when average individual risk increases, so does the spatial variability, deteriorating the benefits of the index insurance. A direct consequence of this is that selecting good zones for index insurance is a difficult task: for one, easy available statistics such as the temporal variance of the zone average[14] are potentially misleading, leading to choose zones where index insurance offers the lowest farm-equivalent coverage. What is clearly needed beyond the variance of county average is information on the spatial variability, which is much harder to obtain in practice.

4.1 Towards better zone design?

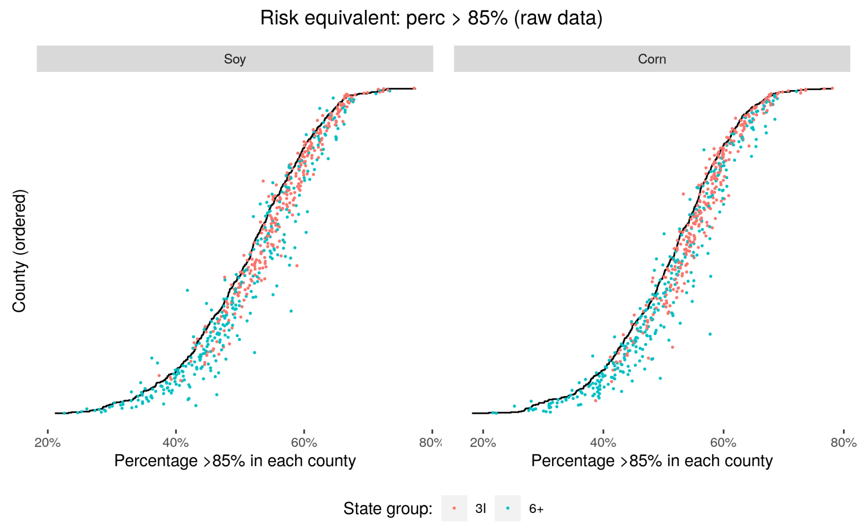
Having investigated the suitability of index insurance in each county, the next question we ask is whether there are gains to be made by redesigning these county zones. The index insurance from RMA uses county boundaries. The reliance on county boundaries is mainly done out of convenience, given that this is the unit considered for official statistics. But there is no reason to believe that these administrative boundaries represent homogeneous regions. Thanks to the geo-referenced dataset we have, we can design more natural zones than the arbitrary county boundaries. This is however challenging computationally, given the huge size of our sample (1.8 M fields), making a full redesign of the entire sample a very hard task. As a first step in this direction, we proceed to a simpler exercise where we seek to split each county into two sub-clusters. While ideally these county sub-clusters would contain spatially-contiguous fields, we take the simpler approach to use standard cluster algorithms that ignore spatial constraints. This will provide an upper bound on the usefulness of sub-county clustering, given that imposing spatial restrictions will decrease the homogeneity of clusters, and thereby likely reduce the improvement in utility of insurance compared to the unrestricted sun-clusters. The exercise is also run separately for corn and soybeans, which provides again an upper bound, given that imposing the more realistic condition that the zone is the same for both crop would further reduce the clustering effectiveness.

A concern about splitting counties into two might be that this is mechanically increasing the usefulness of index insurance by reducing the size of the pool, thereby increasing the weight of each own field in the mean. To make sure our results are not driven by this mechanical artifact, we first did random splits of each county. This gives us a benchmark against which to assess the value of more sophisticated splits. Simulations indicate that this mechanical effect is very small: only for counties with less than 50 fields does a random split noticeably increase the respective R^2, and beyond 100 there is really no difference.

We use various variables to cluster our counties. We consider first clustering on the yields. This should provide the best split, and hence we would

[14] Remember that our measure of temporal variability used here is derived from the average field-level variance, which is not equal to the variance of the average.

Figure 10: Pre- and post-split county utility of insurance: percentage of fields with farm-equivalent coverage above 85%



expect higher improvements from this method. In some contexts with less data, clustering on yields might difficult, so we consider also clustering based on a soil data. We take the soil data from the SSURGO survey, which covers the whole US. We consider their National Commodity Crop Productivity Index (NCCPI) variable, as well as the *root zone available water storage*.

A last concern about the clustering exercise is that the simulated data is simulated under the Miranda's model with one single mean and i.i.d. idiosyncratic errors.[15] Under this model, clustering units should not lead to much improvements in homogeneity. Even clustering low and high betas (fields with low or correlation to the mean) would have little impact, as each subgroup is still constructed to be (weakly) correlated to the same average. To address this issue, we use here the raw data, enforcing premiums to be fair at the field level instead of county level.

Figure **??** shows the results from the clustering exercise, using yields as clustering variable. The black line shows the pre-split *county percentage of fields with farm-equivalent coverage of at least 85%*. The value of the metric is displayed over the x-axis, and counties are ordered along the y-axis. Dots indicate the post-split average measure, that is the average across the two sub-clusters. A dot on the right size of the black line indicates an improvement from splitting. Surprisingly, some counties see a deterioration from splitting, although most of them ($\sim$ 90%) see an improvement. Without surprise, the largest improve-

[15]In fact, the covariance matrix of the data simulated under the i.i.d. model has a so-called *spiked* structure, with on one dominant eigenvalue, and further eigenvalues explaining little remaining variation.

ments tend to happen for the counties that have the initial lowest measures. Conversely, counties with very good farm-equivalent coverage tend to see little improvements. Dots are colored according to whether the state is part of the so-called 3I states (Iowa, Illinois and Indiana) or the six others. The 3I are a weak proxy for the *core* states we described, and tend indeed to have higher initial metric.

Overall, results from the splitting exercise are rather disappointing: the average improvement is just 2% for each crop, indicating that with 2% more of fields would strictly prefer index insurance even over the highest farm-level insurance at 85%. Results for our other metrics (percentage of fields above 50%, or CED ratio of index insurance versus none) are similarly low. These results are particularly disappointing keeping in mind that the clustering is made for each crop separately, and without spatial contiguity. Adding these additional constraints would reduce further the benefits from sub-clustering. https://www.overleaf.com/project/5e5482789438140001249d50

5 Conclusion

In this study, we investigate the suitability of crop insurance in the US using a unique dataset of close to 1.8 million fields observed over 20 years through satellite remote sensing. We run a large-scale simulation seeking to replicate observed yields as closely as possible, yet abstracting from moral hazard or adverse selection issues. We develop several metrics of suitability of index insurance based on expected utility theory, comparing index insurance to no insurance but also to farm-level insurance. Thanks to the very large scale of our dataset spanning close to 600 index insurance *zones*, we investigate then what are the characteristics of the counties which make insurance more beneficial. We finally investigate whether basis risk can be reduced through a zone redesign, splitting each county into two sub-clusters.

Our current results bring both hope and concern about index insurance. On the positive side, our simulations show that absent adverse selection and moral hazard, index insurance brings a positive improvement for almost all fields. When expressed in our new measure of farm-equivalent coverage, index insurance is at least as good as a 50% farm coverage for a majority of fields, indicating that it can serve the basic function of protecting against catastrophic events. Furthermore, when assessed against the highest-available level of 85%, 30% of the fields still benefit more from an index insurance at the 90% coverage level. On the negative side, our results comparing county characteristics and index insurance suitability indicate that where those areas where risk is highest turn out also to be those where index insurance is the least beneficial. This result is explained by the fact that temporal and spatial variability tend to be correlated at the county level, so that counties with highest needs for insurance (high temporal variability) are those where index insurance is the least effective (high spatial variability). As a second negative result, we find that a sub-county clustering approach has little effect on reducing basis risk.

Table 1: Subsidy rate for farm- and area-based plans, yield protection

		Subsidy rate	
Coverage type	Coverage Level	Farm yield	Area yield
Catastrophic	50%	100%	
Additional	50%	67%	
	55%	64%	
	60%	64%	
	65%	59%	
	70%	59%	59%
	75%	55%	59%
	80%	48%	55%
	85%	38%	55%
	90%	-	51%

Source: ~~RMA Insurance Handbook~~

A Appendix

A.1 Supplementary figures

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