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How strong is the "natural hedge"? The effects of crop acreage and aggregation levels.

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Abstract

The level of natural hedge, i.e. the (negative) correlation between price and yield levels, is an important determinant for farmers' income risks and their demand for risk management instruments. The natural hedge is often approximated with correlations observed at more aggregated levels, e.g. the county level. This induces biases because the natural hedge at the farm-level is smaller than on more aggregated levels. In this paper, we put this idea one step forward and investigate the empirical relationship between price-yield correlations and the underlying crop acreage, using farm-level data for 5 crops in Switzerland. We find that, for instance, a 1% increase in area under maize and intensive barley leads to a change in the correlation by -0.02 and -0.08, respectively. Thus, larger farms have a stronger natural hedge. Using a revenue insurance example, we show that this information can be used to adjust insurance premiums for each farm.

Keywords: price-yield correlation, aggregation bias, crop insurance

JEL classification: Q1, G2

1. Introduction and Background

The incomes of farmers, in terms of both their levels and distribution or equity, are one of the major concerns of agricultural policy makers (OECD, 1998). Concerns on increasing farm income volatility caused European policy makers to assess possible risk management tools that can be implemented to support farmers (e.g. Cafiero et al., 2007, Meuwissen et al., 1999, 2008, 2011, OECD, 2009, Bielza Diaz-Caneja et al., 2008, European Commission, 2001). More general, risk management at large is expected to gain importance in agriculture in the coming decades (e.g. Musshoff et al., 2011, Bielza Diaz-Caneja et al., 2008). This is in particular due to increasing production risks caused by changes in climatic conditions (e.g. Torriani et al., 2007) as well as due to increasing price volatility caused by market liberalization (e.g. Mahul, 2003). In order to cope with these risks, market based instruments such as insurances as well as future and option contract markets but also on-farm risk reduction measures may play an even more critical role as risk management tool for farmers.

If dealing with income risks in agricultural production, the so called natural hedge is extremely important for risk considerations and risk management decisions at the farm level. In crop production, the natural hedge is defined as negative price-yield correlation. McKinnon (1967) showed that drivers affecting the physical production of an individual producer (e.g. weather conditions) usually also affect other producers in a specific region. Thus, individual farm output is correlated with aggregate output levels (in a region or country). Finally, this implies that production levels of a single producer are negatively correlated with (local) prices for this product (McKinnon, 1967, Harwood et al., 1999).

Such correlation moderates revenue variability and thus directly influences the degree of income risks and the demand for risk management instruments. For instance, we expect that a higher level of natural hedge reduces farmers' demand for insurance solutions to reduce yield and price risks, respectively. Furthermore, stochastic simulations of farm revenues have to take this effect into account (Artavia et al., 2010). The heterogeneity of the level of natural hedge across farms or regions can also affect the effectiveness of policy measures to reduce income variability such as for deficiency payments that assist farmers if prices are low (Skees et al., 1998). Such policy instruments (or more general policy instruments that aim to reduce farmers' income risks) have been shown to larger affect income variability if the level of natural hedge is low (Skees et al., 1998).

It is widely accepted that the correlation between prices and yields can differ significantly between crops and regions. For instance, low price-yield correlations are expected for a region that is a minor producer (in terms of quantity) for a specific crop in a country (e.g. Skees et al., 1998, Harwood et al., 1999). Thus, the price-yield correlation is usually strongest in areas where most farm-level yields are closely related to production in the area at large (e.g. a large region facing similar environmental conditions) and where the area's production accounts for a significant share of production (Dismukes and Coble, 2006). Also the size and closeness of the market is expected to influence the observed level of natural hedge: small and localized markets, with inelastic demand, are expected to exhibit larger levels of natural hedge (Zentner et al., 2002). Furthermore, for crops that can be stored cheap and effectively the harvest quantity in a specific year may not necessarily have a large influence on market prices in this year.

The estimation of price-yield correlations takes often place at aggregated levels (i.e. at levels higher than the farm-level). Yield-price correlations are, for instance, analyzed by Artavia et al. (2010) in German crop production at the national level, Price and Wetzstein (1999) for peach production in Georgia at the state level, by Li and Vukina (1998) for maize production in North Carolina at the county level, by Hanson et al. (1999) for corn production in Michigan at the county level, by Kurosaki (1997) for various crops in Pakistan at the district level, by Stokes (2000) for Iowa maize production at the state level, and by Zentner et al. (2002) for various crops in Saskatchewan estimated at the province level. Note that the here presented set of studies is incomplete and should only indicate examples, summarizing the enormous amount of empirical work in this area is beyond the scope of this paper. Along these lines, the premium rating methodology of the income protection plan in the USA accounts for the correlation of national prices and county yields, i.e. does not use farm-level correlations (Skees et al., 1998). Of course, there are also studies that focus on price-yield correlations at the farm-level. Farm-level levels of natural hedge have been addressed, for instance, by Kobzar (2006) for various crops in Dutch agriculture, by Coble et al. (2007) for corn, soybeans and cotton production in the USA, by Antón-Lopez and Kimura (2009) for German wheat and barley production, as well as by Mahul (2003) for wheat in two French Regions.

The choice of using aggregated levels is often motivated by the fact that sufficient farm-level data is not available (Kurosaki, 1997). Coble et al. (2007) showed that this choice of working at aggregated levels causes serious problems for farm-level risk analysis and modeling. First, yield variability is smaller at more aggregated levels, caused by the so called aggregation bias (see Finger, 2012a, for an overview of studies on aggregation biases). Second and relevant for this study, the correlation between yields and prices is much larger at more aggregated levels, e.g. if comparing the farm- with the national-level. Coble et al. (2007), for instance, showed that the price-yield correlation for maize in the USA is on average -0.064 if measured at the farm-level but is -0.381 if measured at the national level. These biases arising from data aggregation (including those in estimates of natural hedge) affect the effectiveness of specific insurance solutions (Coble et al., 2007).

With regard to questions of aggregation biases in yield variability estimates, it has been shown that there exist also on-farm aggregation biases, i.e. that specific effects differ across farms according to their farm size. Marra and Schurle (1994), for instance, have shown for Kansas that a 1% decrease in area under wheat leads to a 0.1% increase in standard deviation of wheat yields at an individual farm. Similar elasticities have been also found for Swiss wheat (-

0.11%) and barley (-0.05%) production (Finger, 2012a). A similar on-farm effect is expected to be observable for the level of natural hedge, i.e. production levels on larger farms are expected to have, on average, a stronger influence on crop price developments. Thus, farm size (and potentially other variables) could be an indicator for the level of natural hedge on a specific farm and would thus contribute to a better design of risk management measures and the modeling of farm behavior. Such empirical analyses is, however, not available yet.

Based on this background, the goal of this study is to a) estimate levels of natural hedge, b) analyze their heterogeneity across space and crops, c) provide estimates for errors due to data aggregation, i.e. aggregation biases in price-yield correlations, and d) quantify the on-farm aggregation effects, i.e. the effects of crop acreage of a single producer on his level of natural hedge. The latter point is expected to be of particular importance for the design of insurance solutions: we aim to present continuous empirical relationships that can be used to adjust expected price-yield correlations for individual farms. To underline relevance of this issue, we provide empirical analyses showing the effects of this heterogeneity on a revenue insurance example and provide examples for potential pitfalls of such insurance solutions if the heterogeneities in price-yield correlations caused by heterogeneous crop acreages or by the aggregation of different farms are not considered.

Our analysis is based on empirical examples from Swiss crop production. This choice is motivated by the fact that there is currently a lack of market-based risk management instruments available for Swiss crop producers, also due to the risk mitigating role of subsidies (e.g. El Benni and Finger, 2012). However, recent analyses have addressed new risk management instruments because a higher demand is expected, in particular due to expected changes in production and market risks (e.g., Finger, 2012b, Finger and Calanca, 2011, Torriani et al., 2008). A better understanding of (and empirical knowledge on) natural hedge effects will improve these analyses on potentials and pitfalls of specific risk management instruments. In particular, expectations on insurance demand may differ across crops as well as across producers. The heterogeneity of on-farm yield-price correlations can be a substantial factor for these differences. Our empirical analyses are based on for Swiss maize, barley and wheat producers, representing the three most important crops in Swiss agriculture. Barley and wheat are produced in Switzerland to a large extent extensively (under very restrictive use of agro-chemicals, e.g. Finger 2010a), and intensive and extensive production are thus treated separately in our analysis.

2. METHODOLOGY

The analyses presented in this paper are based on farm-level data that is treated individually or at more aggregated levels. For each farm considered, annual price and yield data for the period 2002-2009 is used. Both price and yield data may exhibit deterministic developments (i.e. trends) over time that can influence estimates of price and yield variability as well as price-yield correlations. In particular for the Swiss situation where increasing yield levels accompany with decreasing price levels, negative price-yield correlations would be overestimated. For each crop, we use (crop)area-weighted averages over all farms to test for trends in crop yields and crop prices. Trends in yields and prices estimated on the aggregated level are used to detrend individual farm-level time series. This strategy ensures that structural developments in price and yield data do not affect price-yield correlation estimates. See Conradt et al. (2012) for a discussion on the use of aggregated yield data for detrending. To reduce the potential influence of outliers, the MM-estimator (a robust regression technique) is used for linear detrending (Finger, 2010b). Based on detrending results, all yield and price values are than set on the level of 2006.

Based on this detrended yield and price time series for each farm, the subsequent analyses are conducted. First of all, farm-level price-yield correlations as well as yield and price variability are calculated and presented. Price-yield correlations are first estimated using Pearson correlation. This Pearson correlation coefficient measures a linear relationship between crop prices and yields. Furthermore, it is sensitive to outlying observations, i.e. observations that deviate from the relationship described by the majority of the data (Finger and Hediger, 2008). To also account for non-linear (or more general, monotonic) relationships and to reduce the potential influence of outliers, we additionally use the Spearman rank correlation coefficient. Both Pearson and Spearman correlation are estimated throughout our analysis and potential differences are discussed.

To estimate the relationship between price-yield correlations and the crop acreage as well as to estimate the effects of data aggregation, two strategies are considered: First, we estimate how a farm's crop acreage influences its price-yield correlations using a regression analysis. To this end, estimated price-yield correlations are used as dependent variable, i.e. each farm leads to a single observation in the data set. The farm's crop acreage is calculated as the average of the available observations in the period 2002-2009. To account for the fact that correlations cannot exceed the range of -1 - +1, Tobit regressions are used throughout the paper. In these regressions, we also account for the specific location of each farm expressed as the canton (Switzerland consists of 26 cantons, with only the minority having significant crop production). The latter factor at large (i.e. not for each specific canton) is tested on significant influence in the regression models by using Chi-Square tests.

To describe empirically the relationship between price-yield correlations and crop acreage, the here employed data from Swiss crop production has two major drawbacks: a) the number of available observations is limited (cp. section 3) and most importantly b) the heterogeneity with respect to crop acreage is small. Swiss agriculture is characterized by small farms with almost no farms with very large crop acreages (cp. section 4). Thus, we expect that the results from the above discussed regressions will not be able to fully reflect the underlying relationship. To overcome this drawback, a bootstrap application is used. In this procedure, we create combinations of randomly selected farms by estimating area weighted yields and prices for each year as well as summing up crop acreages from these farms. Thus, different farms are randomly merged (so that they represent a single farm) in our approach. For each possible number of farms in a sample (n=1,…,N) we create 1000 randomly created combinations from original data. N denotes the total number of farms considered for each crop (cp. data section). Thus, this approach leads to a total number of observations of 141000 for maize, 579000 for intensive wheat, 779000 for extensive wheat, 624000 for intensive barley and 595000 for extensive barley. Based on these data merger from different farms, new price-yield correlations are estimated that are used to re-estimate the relationship between the level of natural hedge and the (total) crop acreage. Two models are estimated: first, crop acreage enters the model linearly; second, it is used in logarithmized form. Models are compared based on log-likelihood values and Wald statistics. Note that this analysis does not account for effects of the location of a farm, because farms are randomly merged across cantonal boundaries. In summary, the initial data sets are used to construct new, large datasets that allow investigating the relationship between price-yield correlations and crop acreage in much more empirical detail and precision.

Finally, we investigate the influence of the specification of the level of natural hedge on the design of a revenue insurance (see e.g. Bielza et al., 2008, for overviews on applications). For simplicity, we use the example of an average farm, where mean and standard deviation of both crop yield and crop price is known. However, the standard deviation of revenues is not known but has to be approximated from the information on price and yield distribution parameters. In addition, we have no farm-level time series of yields and prices and the correlation between these two variables is thus unknown. This situation described above reflects the case that a farm enters an insurance program without sufficient historical farm-level records. Price and yield information, however, can be approximated from other farms, e.g. by using average values across all farms.

This example is now used to investigate four possibilities (scenarios) how to treat the missing information on the level of natural hedge: 1) price-yield correlations are not considered at all for premium calculation, 2) price-yield correlations from the aggregated (i.e. national) level are used to calculate the revenue insurance premium, 3) average farm-level price-yield correlations are used and 4) the regression results on the relationship between the expected price-yield correlation and crop acreage are used to estimated farm-specific revenue insurance premiums.

For illustration purposes, this example focuses on maize. As noted above, we assume that farm-level information on average yield, μ_q , variance of yield, $var(q)$, mean price, μ_p , and price variance, $var(p)$, are known. The variance of gross revenues (gr) can thus be approximated as follows (Bohrnstedt and Goldberger, 1969):

(1) $$Var(gr) = \mu_q^2 var(p) + \mu_p^2 var(q) + 2\mu_p \mu_q cov(p, q)$$

$cov(p, q)$ is the covariance of price and yield, calculated as the product of correlation and both standard deviations. This parameter is subject to the above described scenario analysis. Based on the variance of gross revenue and its average (calculated as product of expected, i.e. average, yields and prices, $\mu_{gr} = \mu_q \, \mu_p$) we are now able to calculate fair insurance premiums. To this end, we assume a coverage level of 90%, i.e. a deductible of 10%. Thus, if the actual revenue (gr_i) falls below the 90th percentile of average revenues (μ_{gr}) the farmer is indemnified. This critical gross revenue level gr_C, i.e. below which the farmer gets a payment from the insurance, is defined as follows: $gr_C = 0.9 \, \mu_{gr}$.

If the revenue gr_i falls below the critical revenue levelgr_C, we assume that farmers' are indemnified linearly. Thus, the indemnity payment function can be described as follows:

(2) $$Indemnity = \max\{0, gr_C - gr_i\}$$

The premium of this insurance is calculated as 'fair premium', i.e. the insurance premium is equal to the expected indemnity payment (Musshoff et al., 2011). For each calculation of an insurance premium, we simulate 10000 revenues based on the expected revenue as well as the information on revenue variance (which differs according to the scenario employed) assuming normal distributions. For scenarios 1-3, this leads to a single estimate for the insurance premium for each scenario. In contrast, we repeat the procedure for scenario 4 according to the observed crop acreages for the 141 maize producers included in our analysis separately. Thus, each farm has an individual revenue insurance premium. Note that yield and price risk are assumed to be equal across these farms, but price yield correlations depend on the individual crop acreage. The latter relationship is taken from the regression analysis described above. From these scenario analyses, the resulting insurance premiums are presented and used as discussion basis for the relevance of better knowledge on levels of natural hedge on the farm-level.

3. DATA

Our empirical case study is based on Swiss FADN data, i.e. farm level bookkeeping records, covering the period 2002-2009 (Agroscope FAT, 2005). Details on the dataset and sampling methodology are presented, for instance, by Meier (2005). Note that price, yield and crop acreage is limited to the farm-level, i.e. no field-level data is available. From this database, those farms are selected that reported yield, price and acreage information for the crop analyzed for at least 4 years in the period 2002-2009. This leads to a set of 141 maize producers (with totally 727 annual observations), 579 intensive wheat producers (with totally 2512 annual observations), 779 extensive wheat producers (with totally 3863 annual observations), 624 intensive barley producers (with totally 2793 annual observations) and to 595 extensive barley producers (with totally 2653 annual observations).

Note that extensive differs from intensive production by the fact that no application of fungicides, plant growth regulators, insecticides and chemical-synthetic stimulators of natural resistance is allowed. This production type is supported by an ecological direct payment since 1992, and the majority (i.e. more than 50%) of wheat producers in Switzerland has adopted it in the last two decades (see Finger and El Benni, 2011). Among the here considered crops, only wheat and barley are included in this ecological direct payment scheme (Finger, 2010a).

4. RESULTS

4.1. Descriptive analyses

Table 1 shows the descriptive statistics of crop yields and prices estimated at the aggregated level, i.e. by using (crop)area-weighted averages over all farms. It shows that differences in yields and prices between extensive and intensive wheat and barley production are large, which further underlines the importance of separated analyses for these categories. In general, we find that crop yields increased (except extensive barley), but crop prices decreased in the considered period 2002-2009. Estimated annual yield increases, however, are small (in the range of 0.48-1.17 dt/year). This is due to the fact that the greening instruments of Swiss agricultural policy, that are applied since the 1990s, have led to much smaller yield growth rates than in earlier periods (Finger, 2010a). Even though trends in yields and prices are not necessarily significant, they have to be removed to ensure that increasing yield levels that are accompanied by decreasing price levels do not lead to an overestimation of negative price-yield correlations. Thus, all subsequently reported means, standard deviations and correlations are based on detrended data.

Price-yield correlations (Pearson) observed at the aggregated level range from -0.17 (extensive wheat) to -0.39 (intensive barley). Thus, there is a substantial level of natural hedge observed at the aggregated level for all crops. Comparing Pearson and Spearman correlations shows that both estimators can differ substantially: Spearman correlation is higher than Pearson correlation for extensive and intensive wheat as well as for intensive barley. This indicates particular non-linear relationships between yields and prices for these crops. In contrast, Pearson correlation was found to be higher for maize and extensive barley.

Table 1. Descriptive statistics of crop yields and prices: aggregated level (area-weighted averages).

	Maize	Intensive Wheat	Extensive Wheat	Intensive Barley	Extensive Barley
Mean Yield (in dt ha^{-1})	95.78	65.11	53.81	71.04	54.02
SD Yield (in dt ha^{-1})	6.57	3.71	3.12	4.21	3.38
Trend Yield (in dt ha^{-1} y^{-1})	1.17	0.60	0.48	0.59	-0.06
Mean Price (in CHF dt^{-1})	44.03	54.95	60.82	43.27	42.60
SD Price (in CHF dt^{-1})	2.46	4.01	4.74	2.61	2.85
Trend Price (in CHF dt^{-1} y^{-1})	-0.97	-1.11	-1.12	-1.00***	-1.07***
Price-Yield correlation (Pearson)	-0.34	-0.30	-0.17	-0.39	-0.25
Price-Yield correlation (Spearman)	-0.31	-0.43	-0.24	-0.55	-0.19

***denotes significance at the 1% level.

Table 2 shows the descriptive statistics based on farm-level analyses. Thus, all values presented in Table 2 represent average values across all farms. Numbers in parentheses represent the sample (across all farms) standard deviations. It shows that standard deviations of crop yields at the farm-level are substantially higher than estimated at the aggregated level (comparing Table 1 and 2). More specifically, yield standard deviation at the farm level is, on average, 2.53, 2.33, 2.36, 2.61 and 2.62 times higher than at the aggregated level for maize, intensive wheat, extensive wheat, intensive barley and extensive barley. This refers to the 'classical' aggregation bias in yield variability (see Marra and Schurle, 1994, and Finger, 2012a).

For price variability, smaller differences between aggregation levels are found: price variability at the farm-level is 2.29 (maize), 1.66 (intensive wheat), 1.71 (extensive wheat), 1.82 (intensive barley) and 1.79 (extensive barley) times larger than on the aggregated level. Even though these aggregation biases in price standard deviation are smaller than for crop yields, they are not negligible. Partially, this is in agreement with the results of Coble et al. (2007) who show that yield variability increases more rapidly than price variability with disaggregation. However, Coble et al. (2007) also state that prices are highly spatially correlated and price variability is thus expected to be similar across a country. Thus, the here found rather large effects of aggregation on price variability are unexpected. The higher price variability at the farm-level is expected to be the result of variable quality levels. For instance, wheat may range between high class baking to fodder quality (see the Swiss cereal producer organization http://www.swissgranum.ch, for details and data) depending on weather conditions and management, which leads to large differences in prices received. Thus, also volatile crop qualities (which remain unobserved in FADN data) can contribute to crop price volatilities at the farm-level. On more aggregated levels, however, we expect that this effect averages-out across farms.

Important for this study, Table 2 also shows that price-yield correlations are smaller at the farm-level: These differences are largest for barley, with a factor of 3.13 for extensive and a factor of 7.80 for intensive barley (both for Pearson correlation). The difference between aggregation levels in price-yield correlation is - by far - smallest for extensive wheat (factor 1.21). For intensive wheat and maize these factors are 2.00 and 1.70, respectively. Even though differences between Pearson and Spearman correlation were found to be large at the aggregated level, virtually no difference between the two estimators is found for the farm-level analysis. Thus, subsequent applications focus on Pearson correlation only.

Table 2. Descriptive statistics of crop yields and prices: farm-level.

	Maize	Intensive Wheat	Extensive Wheat	Intensive Barley	Extensive Barley
Number of Farms included	141	579	779	624	595
Area under the crop (in ha)	2.72 (1.94)	4.63 (3.50)	3.72 (2.86)	2.42 (1.46)	1.97 (1.17)
Mean Yield (in dt ha^{-1})	96.12 (11.91)	63.60 (10.13)	53.26 (7.58)	69.55 (11.09)	54.18 (9.18)
SD Yield (in dt ha^{-1})	16.60 (8.09)	8.64 (5.32)	7.35 (3.71)	10.99 (5.61)	8.87 (4.69)
Mean Price (in CHF dt^{-1})	43.94 (7.70)	53.93 (9.49)	60.21 (15.84)	42.56 (5.97)	42.65 (8.28)
SD Price (in CHF dt^{-1})	5.64 (5.74)	6.66 (5.01)	8.12 (5.39)	4.75 (5.98)	5.09 (5.82)
Mean Revenue (in CHF ha^{-1})	4166.71 (740.44)	3388.52 (614.48)	3149.08 (694.65)	2945.51 (565.65)	2291.45 (522.04)
SD Revenue (in CHF ha^{-1})	811.65 (436.94)	568.97 (316.11)	556.14 (278.17)	566.08 (356.21)	460.06 (286.83)
Price-Yield correlation (Pearson)	-0.20 (0.51)	-0.15 (0.57)	-0.14 (0.53)	-0.05 (0.57)	-0.08 (0.59)
Price-Yield correlation (Spearman)	-0.20 (0.50)	-0.14 (0.56)	-0.14 (0.53)	-0.04 (0.56)	-0.09 (0.58)

Note that all yields and prices are set on the level of 2006 after detrending. Numbers in parentheses represent the sample (across all farms) standard deviations.

In general, the here indicated levels of natural hedge in Swiss crop production tend to be higher than for other countries. This is in particular due to the high level of border protection measures for agricultural products (e.g. tariffs and quotas), which leads to a rather closed economy for agricultural goods. Artavia et al. (2010), for instance, found price-yield correlations in German agriculture at the national level of -0.07, -0.25 and -0.27 for wheat, barley and canola, respectively. Kobzar (2006), estimated yield-price correlations at the farm-level for Dutch agriculture and found, for instance, values of -0.05, -0.03, -0.32, -0.44, -0.38 for wheat, barley, sugarbeets, carrots and table potatoes, respectively. Zentner et al. (2002) found even positive price-yield correlations (in the range of 0.03 – 0.25) for spring wheat, durum, barley and field pea in Saskatchewan estimated at the province level, negative correlations (in the range of -0.15 - -0.20) are indicated in this study for flax, canola, mustard and lentil. A price-yield correlation of -0.08 for Iowa maize production estimated at the state level (futures) has been indicated by Stokes (2000). A much higher level of natural hedge, i.e. -0.52, was found for peaches in Georgia analyzed at the state level (Price and Wetzstein, 1999). For maize in North Carolina using county level data (spot markets), Li and Vukina (1998) found correlations between -0.04 and -0.19. Hanson et al. (1999) indicate a level of natural hedge of -0.32 for corn production in Michigan measured at the county level. Finally, Coble et al. (2007) find, using USA data, correlations for maize to be between -0.064 at the farm and -0.38 at the national level, for soybeans: between -0.10 at the farm and -0.36 at the national level, and finally for cotton: between -0.04 at the farm and -0.14 at the national level.

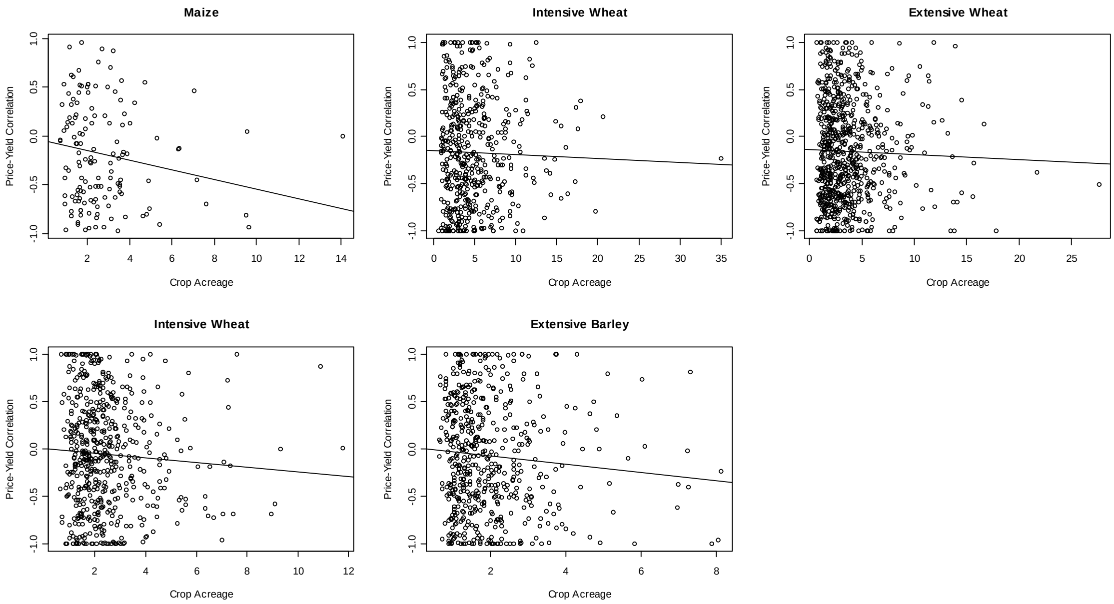
These results underline the expected tendency: special crops such as vegetables and fruits tend to have larger levels of natural hedge. This is due to the usually smaller (in terms of space) market for such products and the shorter durability (and inferior storability) compared to staple crops such as wheat. Along these lines, cereals tend to have the lowest levels of natural hedge. Furthermore, the existing literature underlines the findings of our analysis that the level of natural hedge decreases with lower levels of aggregation (e.g. if going from the national- to the farm-level).

4.2. Explaining heterogeneity in price-yield correlations

In the subsequent step, we aim to explain (at least partially) the heterogeneity in farm-level levels of natural hedge using crop acreage and region as explanatory variables. To this end, Tobit regressions are used. Figure 1 shows the estimated price-yield correlations in relation to the respective area under the specific crop for the 5 crops considered. It shows that the heterogeneity is enormous, i.e. estimates range from -1 to +1. No clear-cut relationship, however, is indicated in the figure with regard to crop acreage.

Table 3 summarizes the Tobit regression results based on the farm-level price-yield correlations and crop acreage. It shows that crop acreage has the expected effect, i.e. larger crop acreage leads to a stronger negative price-yield correlation. Thus, our results indicate that, for a single farm, the level of natural hedge increases with the crop acreage. For instance, a one hectare increase of the area under intensive wheat leads to decrease of the price-yield correlation by -0.005: While the price-yield correlation is, on average, -0.102 for a 1 ha producer, it changes to -0.122 and -0.147 for a farm with 5 ha and 10 ha, respectively, under intensive wheat. Thus, farms with a larger area under a specific crop face lower revenue variability because low and high yield events, respectively, are buffered by higher/lower price levels farmers face. This finding also indicates that larger producers have to rely less on off-farm risk management instruments such as insurances. It shows furthermore, that insurances might have problems with adverse selection, i.e. only small farms with low price-yield correlations (and high yield variability) may take revenue insurance.

Figure 1. Price-yield correlation versus farm-level crop acreage (initial datasets).



However, the effect of crop acreage on price-yield correlations is significant only for the extensive barley model and Pseudo-R^2's remain on small levels. We expect that this insignificance is caused by the small variability in crop acreages observed in our sample: Figure 1 shows that farms with large crop acreages are rare. Furthermore, the number of observations may be still potentially too small to exhibit statistically significant relationships.

Table 3. Tobit regressions explaining observed farm-level price-yield correlations using initial datasets.

	Maize	Intensive Wheat	Extensive Wheat	Intensive Barley	Extensive Barley
Intercept	-0.335 (-0.15)**	-0.097 (0.13)	-0.044 (0.11)	0.075 (0.14)	0.278 (0.17)
Crop acreage (in ha)	-0.024 (0.12)	-0.005 (0.01)	-0.008 (0.01)	-0.008 (0.02)	-0.043 (0.03)*
Influence of (entire) factor canton	***	n.s.	***	n.s.	n.s.
Observations	125	488	680	542	531
McFadden Pseudo R^2	0.08	0.02	0.02	0.01	0.02

McFadden Pseudo R2 compares the relative gain from the full model compared to the intercept (only) model using model log likelihoods. Numbers in parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% level. n.s. denotes not significant. Note that some observations had not been used due to missing values for the variable canton.

To overcome this drawback, we employ a bootstrap approach that creates combinations of randomly selected farms by estimating area weighted yields and prices for each year as well as summing up crop acreages from these farms. Thus, different farms are randomly merged in our approach. This leads to a total number of observations that ranges between 141000 (for maize) to 779000 (for extensive wheat) (cp. Table 4). Based on these data merger from different farms, new price-yield correlations are estimated, which are used to re-estimate the relationship between the level of natural hedge and the (total) crop acreage (see section 2 for a detailed description). Two models are estimated: first, crop acreage enters the model linearly; second, it is used in logarithmized form. For all crops, the second model led to higher log-likelihood values and higher Wald statistics. Thus, only the model results based on logarithmized crop acreages are presented. Note that no differences across cantons are considered here because farms across all cantons are merged randomly in this approach.

Table 4. Tobit regressions explaining farm-level price-yield correlations using bootstrapped datasets.

	Maize	Intensive Wheat	Extensive Wheat	Intensive Barley	Extensive Barley
Intercept	-0.221	0.028	-0.215	0.148	-0.054
ln(Crop acreage)	-0.020	-0.048	0.006	-0.080	-0.029
Number of observations	141000	579000	779000	624000	595000

Table 4 shows the regression results based on the large randomly created datasets. The data as well as the estimated relationships are presented in Figure 2. Due to the high number of (artificially created) observations, all terms are highly significant. Thus, no model goodness of fit and significance levels are presented in Table 4. Coefficients may be interpreted as follows: a one per cent increase in area under maize leads to an increase in the negative price-yield correlation by 0.02. Note that the estimated relationships reflect saturating effects of crop acreages on price-yield correlations (cp. Figure 2).

While regression analyses for maize, intensive wheat and barley as well as extensive barley indicate the expected sign, i.e. a higher level of natural hedge for larger crop acreage, a (slightly) positive relationship is found for extensive wheat. This is in agreement with the descriptive statistics presented in Table 1 and 2, where differences in price-yield correlations between aggregation levels were found to be the smallest for extensive wheat. Thus, there is almost no aggregation effect in price-yield correlations for extensive wheat. This particularity is caused by the fact that the private marketing organization IP SUISSE (www.ipsuisse.ch) markets extensively produced wheat in different distribution channels and pays an additional mark-up on top of market prices for extensive wheat. Therefore, wheat prices received by extensive producers are – on average – higher than for intensive producers (cp. Table 1 and 2). However, the on-the-top payments vary from year-to-year in particular based on the number of contracted farms, as well as marketing of the company. Thus, marketing and price developing mechanisms are different compared to the other crops considered. Note that this price mark-up does not concern extensive barley production because this is focused on bread cereals (barley is used as fodder crop only in Swiss crop production).

The regression results presented in Table 4 can now be used as basis for the adjustment of estimates for farm-level price-yield correlations. For instance, a one hectare maize producer is (based on the regression results) expected to have, on average, a price-yield correlation of -0.22, while a five hectare producer is expected to have a correlation of -0.27.

A first validation approach for these relationships is made by re-estimating the expected price-yield correlations at the farm-level (taken from Table 2, based on average crop acreage) and the aggregated level (taken from Table 1, based on total crop acreage). These comparisons are presented in Table 5. It shows that the regression model is able to predict price-yield correlations very well for most crops.

For instance, the regression model predicts aggregated level price-yield correlations on an average (with respect to crop acreage) farm almost perfectly for maize and extensive barley. For extensive and intensive wheat, farm-level predictions and observations differ by about 0.05 and 0.1, respectively. For intensive barley, however, the absolute difference is still small (about 0.1) but the regression model leads to the wrong sign of the effect, i.e. a positive instead a negative correlation is indicated. For the aggregated level, the performance of the predications based on regression model is much better. Only slight differences in the range of 0.05 are indicated for intensive wheat and barley.

Figure 2. Price-yield correlation versus crop acreage (bootstrapped datasets) and Tobit regression fits (from Table 4).

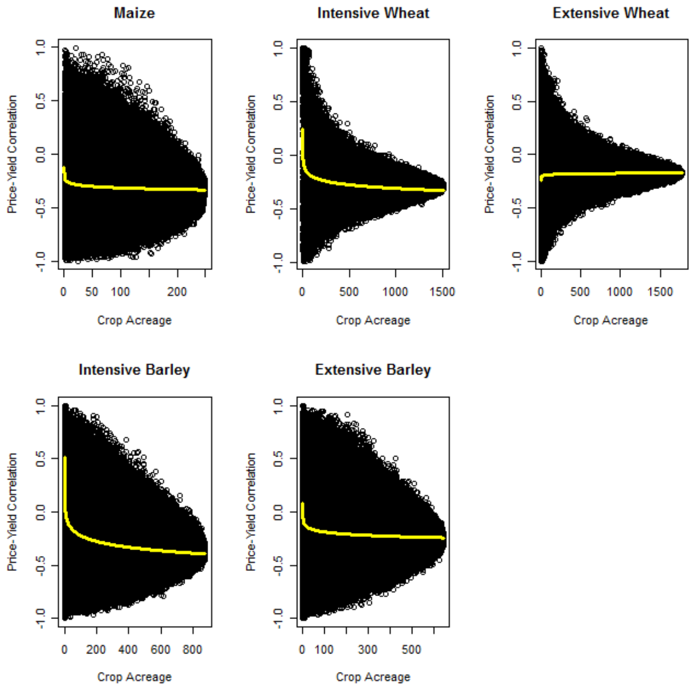


Table 5. Model prediction of price-yield correlation at farm and aggregated level compared to observations.

	Observed correlation (average farm crop acreage) (Tab. 2)	Estimated correlation (average farm crop acreage) (Based on Tab. 4)	Observed correlation (total crop acreage) (Tab. 1)	Estimated correlation (total crop acreage) (Based on Tab. 4)
Maize	-0.20	-0.24	-0.34	-0.34
Int. Wheat	-0.15	-0.05	-0.30	-0.35
Ext. Wheat	-0.14	-0.21	-0.17	-0.17
Int. Barley	-0.05	0.08	-0.39	-0.44
Ext. Barley	-0.08	-0.07	-0.25	-0.26

Note that we are aware that the here analyzed aggregation of crop acreages is only one contributing factor to differences in price-yield correlations. Figure 1 and 2 clearly show that the heterogeneity around regression fits is substantial. However, we think that the empirical relationships between price-yield correlations and the crop acreage considered (e.g. on a farm) presented in Tables 3 and 4 provide interesting insights with high potential for further applications. From earlier studies (e.g. Coble et al., 2007) we were aware that the level of aggregation influences price-yield correlations. The regression results from our analysis can be used to put this idea much more forward: we can now quantify how much larger crop acreage considered (either due to larger on-farm crop acreage or aggregation of several farms) influences this relationship. For instance, we are able to quantify how, on average, a one-hectare producer differs from a ten-hectare producer with regard to the level of natural hedge he faces. This information can be used to adjust farm-level modeling as well as farm-level insurance applications.

4.3. Insurance Example

To empirically illustrate the latter, we investigate the influence of the specification of the level of natural hedge on the design of a revenue insurance that assumes a coverage level of 90%. We use the example of an average maize producer, where only mean and standard deviation of both maize yield and maize price is known. The modeled situation reflects the case that a maize producer enters an insurance program without sufficient historical farm-level records. Price and yield information, however, can be approximated from other farms. Here, we do so by using average values across all farms.

This example is now used to investigate four scenarios how to treat the missing information on the level of natural hedge: 1) price-yield correlations are not considered at all for premium calculation, 2) price-yield correlations from an aggregated (i.e. the national) level are used to calculate the revenue insurance premium, 3) average farm-level price-yield correlations are used and 4) the regression information on the relationship between the expected price-yield correlation and crop acreage are used to estimated farm-specific revenue insurance premiums.

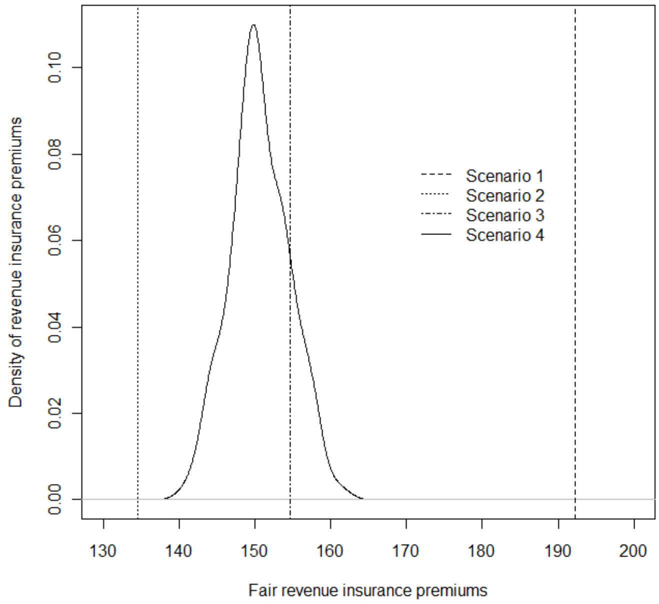
This setup is now used to calculated fair insurance premiums for the four scenarios as described in section 2 and based on farm level estimates on mean and standard deviation of maize yield and maize price taken from Table 2. For scenarios 1-3, this leads to a single estimate for the insurance premium for each scenario. For scenario 4, however, the observed (average) crop acreages of the 141 maize producers included in our analysis are used to calculate expected price yield correlations for each farm separately. For illustration purposes, we assume that even though price yield correlations depend on the individual crop acreage (i.e. have 141 different values), yield and price risk are identical across these farms. The empirical relationship between price yield correlation and the crop acreage is taken from the regression model presented in Table 4. Thus, each farm has an individual revenue insurance premium.

Our results show that if no price-yield correlation is considered, i.e. it is assumed to be zero (Scenario 1), the fair insurance premium is 192.18 CHF ha^{-1} y^{-1}. This is expected to overestimate real revenue risk, because the natural hedge is not considered. If in Scenario 2 price-yield correlations observed at the aggregated level (-0.34, Table 1) are used, the fair insurance premium is equal to 134.54 CHF ha^{-1} y^{-1}. From the above shown bias in price-yield correlations across aggregation levels, we expect that this approach overestimates the influence of the natural hedge on revenue variability at the farm-level. If average farm-level price-yield correlations are used (Scenario 3), the premium is 154.67. The computation of scenario 4 leads to 141 different insurance premiums that range from 140.89 to 161.47. The probability density function of these 141 values as well as the results of scenarios 1-3 are summarized in Figure 3.

It shows that Scenario 1, which does not account at all for natural hedge, overestimates risks and premiums are thus too high. As a result, insurance demand is expected to be low (or zero). In contrast, if price-yield correlations are taken from the aggregated level (Scenario 2), the effect of natural hedge is overestimated, and revenue risk thus underestimated. Premiums tend to be too low, and the insurance will thus suffer from losses because premiums do not cover real indemnity payments. These two cases lead to market failures: either there is no insurance demand or the insurance makes losses. In contrast, if average price-yield correlations are used to account for the influence of natural hedge (Scenario 3), the insurance premium is located in-between the two extreme solutions. This step is expected to avoid the above described market failures to some extent. If insurance premiums are adjusted according to the effect of crop acreage on price-yield correlations for each farm (Scenario 4), insurance pricing is not fixed to a single value but each farm has an individual insurance premium that, on average, leads to a better description of farm-level revenue risks. Even though only the information on crop acreage has been taken into account to adjust premiums, it shows that premiums can differ largely across farms. Thus, this simple adjustment procedure could lead to large potential gains in insurance markets.

In a subsequent step of this research, application to a large set of crops and farms should be provided to show the real impacts of the proposed adjustment procedure. We are aware that heterogeneities across farms with regard to their individual level of natural hedge may be only one part in the puzzle why insurance solutions face market failures. However, the here proposed simple solution to overcome this problem at least to some extent offers a solid starting point for the improvement of insurance design.

Figure 3. Revenue insurance premiums calculated based on 4 different approaches.



5. CONCLUSION

In this paper, we have shown that the level of natural hedge, i.e. the (negative) price-yield correlation differs substantially across aggregation levels based on the example of 5 crops in Swiss agriculture. At the farm-level, much smaller price-yield correlations are observed than at the aggregated (e.g. national) level. Thus, if the price-yield correlations from aggregated levels are used to approximate situations at the farm-level, an error is made. More specifically, the effect of the natural hedge will be overestimated, and farm-level revenue variability will thus be underestimated. In contrast, our results also show that the price-yield correlations are relevant. Thus, not accounting at all for the natural hedge may also cause serious biases in risk assessment and modelling because farm-level revenue variability will be significantly overestimated. To overcome the potential problems described above, farm-level estimates of price-yield correlations should be employed. We illustrate the potential gain from this information using an example of revenue insurance, where an under- or overestimation of insurance premiums can be avoided if a farm-level estimate for the price-yield correlation is used. If necessary farm-level data is missing, a conversion factor that accounts for the structural difference between estimates, for instance, at the national level and the farm-level should be applied.

Furthermore, we have shown that there is a relationship between the price-yield correlation at the farm-level and the respective crop acreage. It shows that larger producers face a higher level of natural hedge. We find that, for instance, a 1% increase in area under maize and intensive barley leads to a change in the correlation by -0.02 and -0.08, respectively. Even though the crop acreage explains the observed heterogeneity in price-yield correlations at the farm-level only to a limited extent, we think that this information can be valuable. We prose that approximations for farm-level price-yield correlations (if real values are not known) could employ this information on crop acreage. We illustrate this procedure for premium calculation in a revenue insurance example. It shows that this simple adjustment procedure already implies large differences in fair insurance premiums across farms. Thus, this simple adjustment procedure (only information on the crop acreage is required) could lead to improved insurance designs and thus avoid insurance market failures.

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