Income Risk of German Farms and its Drivers

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Abstract

The analysis of income risk is the basis for successful whole farm risk management. The measurement of risks helps to objectively assess the farms' individual risk exposure. However, due to limited data availability, comprehensive overall risk analyses are often scarce, e.g. for Germany. The present study analyses risk exposure for more than 3,000 farms in Germany in the period 1996/97-2015/16 on the basis of the national Farm Accountancy Data Network (FADN). Our results show that (i) risk exposure is heterogeneous and that fluctuations and particularly large decreases in farm income are rarely attributable to individual risk components (e. g. prices or yields), (ii) farm income risk has been higher in the period after 2007 for many farms, especially arable and dairy farms, (iii) while the income risk in dairy farming increased, it is still lower than that of most other farm types in the period 2006/07-2015/16, (iv) the formation of expected values has a significant influence on the absolute level of the measured risk and should be given more attention in future research.

Key Words

risk exposition; income risk; farm level risk; severe events; risk components

1 Introduction

Business and especially farming have always been risky. However, risks for European as well as German farmers are widely believed to increase, due to an expected rise of extreme weather events as a consequence of climate change (GÖMANN et al., 2015; DEUTSCHER WETTERDIENST, 2018; TRNKA et al., 2014) as well as further market liberalisation and the increased exposure to the variability of world market prices (LEDEBUR and SCHMITZ, 2012; EUROPEAN COMMISSION, 2017a; FILLER et al., 2010; KEANE and O'CONNOR, 2009). These changes need to be adequately addressed by risk management to limit the danger of illiquidity of the farming business and/or severe reductions of the consumption possibilities of the farm household. The first step in this process is the analysis and quantification of risks (KUNREUTHER, 1976; MUẞHOFF and HIRSCHAUER, 2016). The quantification of one's exposure to risk is a precondition to measure changes in risk, to set goals, compare farms and evaluate risk management instruments. However, quantifying risk is often methodologically challenging. In addition, behavioural economists show that human subjective risk perception is often biased (KAHNEMAN, 2011; SUNSTEIN and ZECKHAUSER, 2011) which is especially valid for extreme events (KUNREUTHER et al., 2001; BUZBY et al., 1994). A description of farmers' risk exposition[1] can help to overcome subjectivity and support an effective risk management.

Given the widely accepted probabilistic definition of risk (OECD, 2009; CHAVAS, 2004; MUẞHOFF and HIRSCHAUER, 2016), risk is characterized by the distribution of all possible outcomes and their probabilities. The majority of humans perceive risk as the threat of a bad outcome or damage (WEBER et al., 2017; BERG and STARP, 2006). While bad outcomes only can exist if there are good outcomes, often bad outcomes are more relevant for risk management than good outcomes (HARDAKER et al., 2015). Therefore, it is useful to measure both risk based on the whole distribution and downside risk.

The measurement of farmers' risk exposure faces two major challenges: first, because risk is typically measured based on the deviations from the central tendency, i.e. expectation, risk depends on properly characterizing the expected value (JUST and RAUSSER, 2002). Thus, a mischaracterization of the expected value may lead to seriously biased conclusions from the risk analysis (JUST and RAUSSER, 2002). The appropriate characterization of expected values is often difficult, because the formation of future expectations

[1] The term „risk exposition" originally referred to quantifying agents' risk expressed in units of money on stake (ADLER and DUMAS, 1984). However, the recent literature widened the term to a concept of objectively describing and measuring the main risks and uncertainties affecting an economic agent, based on the expected distribution or variability of income or its components (OECD, 2009).

differs across individual farmers (JUST and RAUSSER, 2002). A variety of expectation formation methods[2] to model individual behaviour exist (NERLOVE and BESSLER, 2001; JUST and RAUSSER, 2002). Often risk analysis studies use either a linear trend based on the considered period (EL BENNI and FINGER, 2013; EUROPEAN COMMISSION, 2017b) or a floating mean (EL BENNI and FINGER, 2014). However, empirical studies often ignore the critical dependence of risk measurement on the choice for expectation modelling (JUST and RAUSSSER, 2002). Some studies analysing the income stabilisation tool (IST; EUROPEAN COMMISSION, 2013) apply different approaches (e.g., average historical values or regressions based on historical values; FINGER and EL BENNI, 2014; TRESTINI et al., 2018; PIGEON et al., 2014) for establishing a reference income, which implicitly suggests different choices for expectation modelling. However, to our knowledge no study exists which explicitly quantifies farmers risk exposition in the light of different expected value formation methods. The second problem is that a full description of risk encompasses the probabilities and extent of all possible outcomes, which usually results in a vast number of figures difficult to process. The challenge thus is to condense the essential information in a finite set of risk measures while avoiding high information losses.

Whereas risk exposition describes each farmer's risk, existing literature however overwhelmingly focusses on risk at aggregated level, e.g. national prices or regional yields. FINGER (2012) and OECD (2009) stress that the assessment of risk faced by farmers requires data of individual farmers because the aggregation of economic independent farms can lead to crucial underestimation in risk. The few studies which examine risks at farm level are often restricted to the isolated analysis of specific aspects, e.g. yields (GÖMANN et al., 2015; HEIDECKE et al., 2017; LÜTTGER and FEIKE, 2018; ALBERS et al., 2017) or prices (LEDEBUR and SCHMITZ, 2012; KEANE and O'CONNOR, 2009; FILLER et al., 2010). For three reasons it is important to follow a holistic approach instead of just a single risk component approach in farm risk analysis. First, an extreme event is only relevant if it has an impact on overall targets (e.g. level of income variability). Second, the risk of an economic target value like farmers' income is the result of different risky components – like price and yields – which are crucial individual parameters to control the risk of the overall target (MARKOWITZ, 1952; TURVEY, 2012; DE MEY et al., 2016). Thus, the analysis of just income risk alone is also not sufficient to facilitate the comprehension and the management of the risks faced. Third, different risk components, especially prices and yields, are interdependent which can influence the level of risk substantially (KIMURA et al., 2010). A whole farm approach is especially relevant if farms are diversified. Managing risk on a single risk component basis and ignoring whole-farm consequences may result in increasing risk rather than decreasing it (DOMS et al., 2018; MUßHOFF and HIRSCHAUER, 2016).

A major problem is that the availability of historical time series of individual household data for farmers is very limited. Only a few countries in the Farm Accountancy Data Network (FADN) like the Netherlands, Switzerland and the UK have this data (DE MEY et al., 2016). Even if one focuses on farm-level income only, data is limited (OECD, 2011), and studies are often based on less than ten years of observations (EL BENNI and FINGER, 2014; TRIBL and HAMBRUSCH, 2012; MEHRLÄNDERPROJEKT, 2013; BAHRS, 2011; SEVERINI et al., 2017; DE MEY et al., 2016; SEVERINI et al., 2019). Thus, empirical studies at farm-level, which cover income risk and its interactions with drivers like yield and price fluctuations are rare, particularly in peer reviewed journals, even though such analyses are generally recommended (OECD, 2009). The results of farm-level risk analysis show that farm income risk differs between regions and farm types (MEHRLÄNDERPROJEKT, 2013; VROLIJK et al., 2009; TRIBL and HAMBRUSCH, 2012; EUROPEAN COMMISSION, 2017b; SEVERINI et al., 2019; PIGEON et al., 2014; POON and WEERSINK, 2011; EL BENNI et al., 2012). Among different farm types the highest income risk is observed in intensive livestock (EU-wide study by VROLIJK et al., 2009; EUROPEAN COMMISSION, 2017b) or in crop production (Austrian study by TRIBL and HAMBRUSCH, 2012). However, differences between farms of one farm type are substantial, too. In Switzerland and Austria, most risk results from revenue, which in turn is more influenced by price risk than yield risk (TRIBL and HAMBRUSCH, 2012; EL BENNI and FINGER, 2014).

Most known studies conducting comprehensive farm-level risk analysis use data from 2009 or older.

[2] Key methods include extrapolative, adaptive, moving average, future price, ARIMA-model, rational expectations, quasi-rational expectations; for further details see NERLOVE and BESSLER (2001) and JUST and RAUSSER (2002).

Since a structural break in price development on agricultural markets occurred after 2007 (LEDEBUR and SCHMITZ, 2012; KEANE and O'CONNOR, 2009; TADESSE et al., 2014; PIESSE and THIRTLE, 2009; WORLD BANK, 2012), it remains an open question if and to what extent these changes had an impact on farmers' risk exposition. In addition, although severe income declines are of crucial importance for farmers, little attention is paid to the occurrence of extreme price and yield drops and their impact on income in the existing literature. For Germany – a country of 250,000 farms – only one comprehensive risk analysis across different regions and farm types based on recent data is known (EUROPEAN COMMISSION, 2017b). However, a decomposition of income risk in its components has not been conducted for Germany even though climatic and economic conditions differ from those in other countries.

This paper focuses on the analysis of the risk environment of farms. However, in agriculture the farm household is often considered as the decision-making unit, and thus risk assessment and management will be determined by the household objectives, household resources (assets, income sources) and household adaption possibilities (e.g. shifting investments or consumption over time, accumulating or depleting savings; OECD, 2009). The existence of off-farm income may lead to household risk balancing, which DE MEY et al. (2016) found to be a prevalent strategy in smaller farms in Switzerland. As the available data for Germany does not include reliable information on the level of off-farm income, we restrict our income risk analysis to full time farms, where the importance of farm income for total household income is generally higher. The observed risks at farm-level are important information for risk management on household level, even when there is off-farm income. Normative recommendations regarding risk management strategies, which are beyond the scope of this paper, however, need to take into account off-farm income as well as individual risk preferences and objective functions.

Against this background, the overall objective of this paper is to provide a quantification of farm-level income, price and yield risk for German farms pre- and post-2007. For the analysis we use a multi-year data set over 3,000 farms for the years 1996/97-2015/16, provided by the Farm Accountancy Data Network (FADN) of the Federal Ministry of Food and Agriculture of Germany. In addition to farm income risk, we analyse price risk for 13 and yield risk for eight agricultural products. We quantify the realized (observed) risk by measuring both the fluctuation (coefficient of variation) and the frequency of severe events (at least 30% below the expected value). We calculate the contribution of different risk components, including prices, yields, revenues and costs, to the overall income risk. By comparing the periods 1996/97-2005/06 and 2006/07-2015/16, we determine how risks have changed over time, i.e. how risk levels differ between the ten periods before and after the year 2007, which is the year of structural break on agricultural markets. We confirm robustness of our results by applying robust statistical measures and different methods for expected value formation, which include a 'naïve' expected value based on past observations and a linear trend encompassing the whole period 1996/97-2015/16.

Our strategy is as follows: first methodology and data are described. Afterwards we present our results starting with risk measures for prices, yields and farm income risk for different products and farm types, respectively. Then we decompose farm income risk into four basic income risk components and revenue risk into yield and output price risk, and quantify the effect of each risk component on severe income drops. The paper ends with our discussion and conclusions on risk analysis of German farms.

2 Method

First, methods for expectation formation are presented, second risk measures are derived and finally methods to quantify the contribution of risk components on income are considered.

2.1 Formation of the Expected Value

For yields it seems reasonable to assume that farmers are aware of long-term trends due to technical progress and environmental changes. Thus, farmers' expectation is formed by detrending yields with a linear trend[3] (PELKA and MUßHOFF, 2013; VROLIJK et al., 2009). Our time series variable, in this case yield, of farm i in year t is denoted by x_{it}. We estimate the yearly change of yield b_1 for aggregated mean yield over all farms in year t $\bar{x}_t$ with MM regression (YOHAI, 1987): $\bar{x}_t = constant + b_1 * t + e_t$. The

[3] While some studies apply flexible polynomial models JUST and WENINGER (1999) or quadratic models FINGER (2010a), we use a linear trend for our study because our time series is too short to estimate long term changes in trend growth rates.

error term is denoted by e_t. MM regression is a robust estimation technique downweighting outliers which leads to more precise trend estimations especially for short time series (FINGER, 2010b). To account for the individual farm-level yield level we take into account a relative trend b_{i1}^{rel} (Equation (1)) calculated with the mean yield of farm i over all years $\overline{x}_i$. Equation (2) shows the expected value formation based on the aggregated trend with the estimate b_{1i}^{rel}, where t^* is a reference year, i.e. the mean year of each time period.

$$b_{1i}^{rel} = \frac{b_1}{\overline{x}} * \overline{x}_i \quad (1)$$

$$E(x_{it})^{trend,aggregated} = \frac{1}{T}\sum_{t=1}^{T} x_{it} + (t^* - t) * b_{1i}^{rel} \quad (2)$$

Prices and incomes are deflated by the consumer price index provided by STATISTISCHES BUNDESAMT (2017a). Expected values of income and prices are formed by two alternative approaches. The first approach is to conduct a linear detrending. The linear trend is based on the assumption that the farmer is able to derive a long-term trend for a certain period. While the linear trend for aggregated prices is derived equivalent to yields (Equation (2)), detrending of income is based on farm-individual trend to account for farm individual factors (VROLIJK et al., 2009). An individual trend is generated by MM regression: $x_{it} = constant_i + b_{1i} * t + e_{it}$. The expected value $E(x_{it})^{trend,individual}$ is calculated as:

$$E(x)_{it}^{trend,individual} = constant_i + b_{1i} * t \quad (3)$$

Linear detrending is widespread, straightforward and comprehensible, but it may not be appropriate for deriving expected values for prices and income especially if structural changes occur, like the prices explosion in 2007/2008 or the liberalisation of agricultural markets (LEDEBUR and SCHMITZ, 2012; FILLER et al., 2010).

The second approach to expectation formation relies on a model called 'adaptive expectation formation' (NERLOVE and BESSLER, 2001). The adaptive expectation formation is based on the assumption that farmers apply a simple heuristic and predict the future based on the past ('naïve' expectations). Advantages of the adaptive formation are that the model is sensitive to recent years and the implementation straightforward. The first adaptive model $adap1$ incorporates one past observation:

$$E(x)_{it}^{adap1} = x_{it-1} \quad (4)$$

Our second adaptive model $adap3$ incorporates three preceding observations with weights of 0.55, 0.3 and 0.15[4,5]. The adaptive expected value $E(x_{it})^{adap3}$ is calculated as follows:

$$E(x)_{it}^{adap3} = 0.55x_{it-1} + 0.30x_{it-2} + 0.15x_{it-3} \quad (5)$$

A further method for forming expected values is the use of future prices. We do not use future prices for three reasons. First, futures prices are only available for a few products. Second, the use of futures in German agriculture was rather uncommon in SP1. Thirdly, there is a high basis risk to the Matif.

Autocorrelation in time series is generally seen as a relevant factor influencing farmers' expectations (NERLOVE and BESSLER, 2001), even though the extent to which farmers can consider autocorrelation or cycles in their planning is discussed controversially in the literature (PARKER and SHONKWILER, 2014; BERG and HUFFAKER, 2015). The Generalized Durbin-Watson test shows that some autocorrelation is included in our original time series, which can be very different in nature (see Annex 1[6]). Prices of most crops contain positive autocorrelation of order 1, while hog and piglet prices exhibit some higher order autocorrelation (≥4) indicating cyclical patterns. Income autocorrelation is observed for mixed farms (order 1) and for dairy, pig & poultry and other

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[4] Weights and number of observations are based on LOUHICHI et al. (2018). We tested different number of observations and weights. For observations which only have 2 past observations we assumed a weight of 0.66 for x_{t-1} and 0.34 for x_{t-2}. For observations which only have one past observation we assumed a weight of 1 for x_{t-1}.

[5] $adap1$ and $adap3$ were chosen to illustrate the sensitivity of our results to the number of past observations used as a basis for the formation of expectations. $adap2$ and $adap4$ have similar results like $adap1$ and $adap3$.

[6] Annex 1 and the consecutive Annex is provided in a separate file on https://www.thuenen.de/media/institute/ma/Downloads/Duden_Offermann_GJAE2020_Annex.pdf.

grazing livestock farms (order ≥3), while for crops and horticulture farms there is no evidence of autocorrelation of incomes. After the application of the adaptive expectations approach $adap3$ positive autocorrelation up to order 3 is substantially reduced (see Annex 1). Taking into account cyclical patterns of higher order could reduce the estimated risks, however available time series are too short to reliably do so.[7] Also, important cycles like the swine cycle (HANAU, 1928) depend on production cycles of less than a year, and thus become blurred in annual data used for this study.

2.2 Risk Measures

Two different risk measures are calculated: risk is measured by the coefficient of variation and the probability for "severe" downside risk.

a) The coefficient of variation (CV) is a measure of fluctuation. It is calculated as the standard deviation σ_{x_i} divided by the mean expected value of each farm $\overline{E(x)_i}$, and thus is a relative measure which facilitates comparisons of fluctuations between different samples and variables as it is independent of scale. We choose the CV because it allows to measure fluctuations around the expected value and is widely used in the literature (e.g. EL BENNI and FINGER, 2014), which facilitates the comparison of our results to those of other studies.

b) As a second measure we calculate the probability for "severe" downside risk because extreme negative deviations are of extraordinary relevance for farmers. As severe we define a negative deviation of more than 30% from the expected value, based on the standard loss threshold establishing eligibility for many European disaster and risk instruments (EUROPEAN COMMISSION, 2013). Negative deviations of more than 30% are counted per farm and divided by the total number of observations per farm. In risk literature this measure is also called the lower partial moment of order zero[8] $LPM(30)^0$ and formalized as in Equation (6) (MUßHOFF and HIRSCHAUER, 2016). We choose the LPM^0 instead of other measures for extreme events (like the LPM^1 or the *Value at risk)*, because such a measure is often used to measure extreme events (GROSSI and KUNREUTHER, 2005) and is also easily interpreted by humans (UNSER, 2000).

$$LPM(30)_i^0 = \frac{1}{T}\sum_{t=1}^{T} z_{it} \begin{cases} z_{it} = 1\,, if\ -0.3 - \dfrac{x_{it} - E(x)_{it}}{E(x)_{it}} > 0 \\ z_{it} = 0\,, if\ -0.3 - \dfrac{x_{it} - E(x)_{it}}{E(x)_{it}} \leq 0 \end{cases} \quad (6)$$

2.3 Income Risk Decomposition

To identify sources of risks and starting points for effective risk management, we discuss how income risk is decomposed into its components. First, we describe the decomposition of the variance of farm income risk and then suggest an approach which allows to trace severe income declines back to their sources.

2.3.1 Variance

Variance of income is decomposed into sales revenue, other revenue, material costs and other costs (see details of components in Annex 2). The variance of income can be decomposed into the variance of each additive connected component, i.e. variance of random variable X_c, plus the interaction between these components, i.e. covariance between X_c and X_d (SACHS, 2002):

$$Var(Income)_i = \sum_{c=1}^{C} Var(X_c)_i + \sum_{c=1}^{C}\sum_{d<c}^{C} 2Cov(X_c, X_d)_i \quad (7)$$

Equation (7) shows the absolute extent of variance contribution. By dividing the absolute contribution of component c by the total variance of income we obtain the relative contribution of each component.

[7] We did not apply ARMA model as these would require a higher number of observations (50 observations and more, BOX and JENKINS, 1970) than available, which is a common restriction of farm-level analyses (EL BENNI and FINGER, 2013; EL BENNI and FINGER, 2014; SEVERINI et al., 2019).

[8] In catastrophic modelling literature this measure is also called 'exceedance probability' and is recommended to quantify catastrophic risk (GROSSI and KUNREUTHER, 2005; KUNREUTHER, 2002).

The relative direct variance effect $direct(X_c)$ and the covariance effect, i.e. interaction effect $interact(X_{c,}X_d)$, are presented as a percentage of income variance:

$$100\% = \left(\sum_{c=1}^{C}\left(\frac{Var(X_c)_i}{Var(Income)_i}\right) + \sum_{c=1}^{C}\sum_{d<c}^{C}\left(\frac{2Cov(X_{c,}X_d)_i}{Var(Income)_i}\right)\right) * 100\% = \left(\sum_{c=1}^{C} direct(X_c)_i + \sum_{c=1}^{C}\sum_{d<c}^{C} interact(X_{c,}X_d)_i\right) * 100\% \tag{8}$$

Disentangling the variance of revenue into a price component X_p and a yield component X_y requires a different approach than income decomposition because prices and yields are multiplicatively connected. In such cases, a decomposition is done following an approximation approach developed by BOHRNSTEDT and GOLDBERGER (1969), BURT and FINLEY (1968) and GOODMAN (1960) based on a Taylor series expansion (applied in agriculture by SCHMIT et al., 2001, and EL BENNI and FINGER, 2014). Variance of revenue, defined as price times yield, can be determined by:

$$Var(revenue)_i \approx \overline{E(X_p)}_i^2 * Var(X_y)_i + \overline{E(X_y)}_i^2 * Var(X_p)_i + \overline{E(X_p)}_i * \overline{E(X_y)}_i * 2Cov(X_p, X_y)_i \tag{9}$$

Based on the decomposition of Equation (9) relative effects are calculated equivalent to Equation (8):

$$100\% \approx \left(\left(\frac{\overline{E(X_p)}_i^2 * Var(X_y)_i}{Var(revenue)_i}\right) + \left(\frac{\overline{E(X_y)}_i^2 * Var(X_p)_i}{Var(revenue)_i}\right) + \left(\frac{\overline{E(X_p)}_i * \overline{E(X_y)}_i * 2Cov(X_p, X_y)_i}{Var(revenue)_i}\right)\right) * 100\% = \left(direct(X_y)_i + direct(X_p)_i + interact(X_y, X_p)_i\right) * 100\% \tag{10}$$

Using formula (10), the effects add up to the exact variance of revenue only in the case of normally distributed series of price and yields components, otherwise it is an approximation.

2.3.2 Severe Events

To quantify the contribution of severe events at risk component level (defined as event B) to a severe income decline (event A) we apply the concept of conditional probability $P(A|B)$, which gives us the probaility that a farmer observes a severe income decline if event B is true. The conditional probability is calculated as Equation (11) (SACHS, 2002), where the agricultural income is denoted as ϕ:

$$P(A|B)_i = \frac{P(A \cap B)_i}{P(B)_i}$$
$$A := \left\{x_{it}^{\phi} \,\middle|\, \frac{x_{it}^{\phi} - E(x^{\phi})_{it}}{E(x^{\phi})_{it}} \le crit_A\right\} \tag{11}$$
$$B := \left\{x_{it} \,\middle|\, \frac{x_{it} - E(x)_{it}}{E(x)_{it}} \le crit_B\right\}$$

Event A is defined as the relative deviation of income being less than critical value $crit_A = -0.3$. Equivalent the critical value for event B is set to $crit_B = -0.3$ Probabilities are calculated by taking the relative frequency of respective events.

2.4 Statistics and Hypothesis Tests

While risk measures and variance components are calculated for every single farm we evaluate the central value for the whole farm sample by using the 20% trimmed mean. The trimmed mean is more suitable than the arithmetic mean when it comes to outliers, skewness or fat tails (OOSTERHOFF, 1994; WILCOX, 2017). A level of 20% trimming results from a balance between information loss and robustness (WILCOX, 1996).[9] We use the 20% trimmed mean rather than the median as it robust for our samples but the loss of power/efficiency is less than for the median.

[9] A sensitivity analysis shows that our results are robust to different trimming values.

Based on trimmed means, hypothesis tests are conducted while assuming that our sample is a random sample of the population in terms of risk exposition. In case of comparing different periods, methods and farm types we apply bootstrapped confidence interval based on the Yuen test (YUEN, 1974) for dependent and independent groups, respectively, which has been adopted in agricultural economics previously (FINGER, 2012).[10] The bootstrap (and trimmed mean) is chosen because it does not rely on distributional assumptions. The bootstrap method confidence intervals are derived from generating 599 new samples with replacement out of the original sample. A multiple group comparison which is needed for comparing expected value elicitation methods is applied by adjusting p-values with Holm's method (HOLM, 1979).

Risk analysis is conducted with SAS 9.4, whereas hypothesis tests are implemented in R.

3 Data

Risk analysis is done with data of the national FADN provided by German Federal Ministry for Food and Agriculture. The stratified and unbalanced sample includes 20 years of data (1996/97-2015/16[11]). FADN-farms are selected in order to represent farm groups of a country (defined by economic size, farm type and region). The farm accounts include farm-level financial data and physical data. More than 10,000 German farms are included in the sample each year. The composition of the sample changes every year due to changing farm participation, by replacement of approx. 500 farms.

The sample of subperiod one (SP1) includes farms which have at least seven records in 1996/97-2005/06, and similarly the sample of subperiod two (SP2) which have at least seven records in 2006/07-2015/16. The sample of the total period (TP) of 1996/97-2015/16 includes those farms for which the conditions for subperiod one and two are fulfilled. The number of seven is selected to balance between the objective of having long time series and the objective of keeping a high number of farms in the samples.

We select samples for price and yield analysis trying to balance a large sample size and explanatory power (Table 1). For each product analysed, we choose two samples – one for yields and one for prices – to maximize the number of farms which provide data on the subject of interest. We ensure that only farms are selected which exceed certain minimum size[12] with regard to the production of the respective product. Due to lack of data in yields of animal production we do not provide results on animal yield risk. The sample size for prices and yields varies between 46 farms (egg price) and 2,500 farms (wheat yield) and between an average of 17.7 and 18.7 observations per farm. The observations per year vary because there are often fewer observations in the first years and the last years of the period 1996/97-2015/16 than in the rest of the period.

As an income indicator, we use the accounting profit per farm. Therefore, for the income analysis, legal persons (GmbH, AG, KGaA, eG) are excluded from the sample, because they have incomparable income metrics. Part-time farmers are excluded because the agricultural income risk is not as relevant for these farms due to the small share in household income. Farms with an average income below the existence minimum of 16,980 € (="Regelsatz" plus "Teilhabe", education and heating costs) (BUNDESMINISTERIUM FÜR FINANZEN, 2015) are excluded from the sample. If farms do not reach such an average level over the period of at least 14 years, we assume that these farms have significant other sources of income and are not the focus of our study. The results are differentiated by the specialisation of farms, because specialisation has a major influence on risk exposition (e.g. EUROPEAN COMMISSION, 2017b). Thus, according to EU- typology (EUROPEAN COMMISSION, 2008) specialisation in crops, horticulture, dairy, other grazing livestock and pig & poultry as well as no specialisation, i.e. mixed farms, are distinguished. "Mixed" refers to farms which have several branches of production, but no branch of production predominates in economic terms. Table 2 provides an overview of

[10] See WILCOX (2017) for further details. In addition, a verification of results is conducted with the Wilcoxon sign rank test (WILCOXON, 1945) and Wilcoxon sum rank test, respectively, comparing the median of sample distribution.

[11] The farm accounts refer to the German agricultural economic year (farming year).

[12] Minimum size: wheat, winter barley, summer barley, rye, corn, rapeseed ≥2 ha; sugarbeet, potatoes ≥1 ha; head of cows, head of beef ≥10; head of fattened pigs, head of piglet ≥20; head of layer ≥50 (details in Annex 3)

Table 1. Summary statistics of the farm samples for price and yield risk analysis (prices deflated to 2016)

	Sample for Prices							Sample for Yields						
	Farms				Obs. per farm	Mean[1] price		Farms				Obs. per farm	Mean[1] yield	
	Total period (N)	Per year						Total period (N)	Per year					
		Mean	Min	Max					Mean	Min	Max			
Wheat	1,801	1,663	1,271	1,754	18.5		158	2,500	2,329	1,820	2,453	18.6		7.1
Wint. barley	875	792	576	849	18.1		139	2,107	1,942	1,516	2,056	18.4		6.4
Sum. barley	362	325	239	355	17.9		163	562	508	385	550	18.1		5.1
Rye	411	369	266	401	17.9	€/t	135	488	440	315	473	18	t/ha	5.5
Corn	155	134	95	149	17.3		149	191	169	120	186	17.7		8.8
Rapsseed	1,081	984	670	1,056	18.2		309	1,098	1,001	678	1,075	18.2		3.7
Sugarbeet	883	823	603	873	18.6		52	886	826	605	876	18.6		62
Potatoes	242	221	154	241	18.2		120	244	223	155	243	18.3		34
Milk	1,847	1,730	1,332	1,826	18.7	€/t	366	N.A.						
Beef	401	364	270	391	18.2	€/head	1,171	N.A.						
Hogs	705	649	482	698	18.4	€/head	148	N.A.						
Piglets	336	306	219	329	18.2	€/head	59	N.A.						
Eggs	46	42	29	46	18.2	€/egg	0.14	N.A.						

1) 20% trimmed mean
Source: own calculations based on FADN data

Table 2. Summary statistics of the farm sample for income risk analysis (income deflated to 2016)

	Farms					Obs. per farm	Income (€/farm)		
	Total Period (N)		Per year						
	Sample	Germany[2]	Mean	Min	Max		Mean[1]	P25	P75
All	1,755 (100%)	275,000 (100%)	1,607	1,175	1,722	18.3	51,043	32,928	74,423
Crops	453 (26%)	83,900 (33%)	421	294	447	18.6	66,497	40,481	94,615
Horticulture	159 (9%)	6,400 (3%)	146	108	159	18.3	46,954	32,040	70,543
Dairy	624 (36%)	53,100 (21%)	575	432	618	18.4	47,753	32,038	66,270
Other grazing livestock	75 (4%)	60,900 (24%)	68	49	74	18.2	40,761	27,998	55,685
Pig & Poultry	116 (7%)	1,600 (6%)	101	54	116	17.5	50,895	33,613	75,182
Mixed	328 (19%)	35,300 (14%)	296	224	319	18.0	45,137	29,194	66,440

1) 20% trimmed mean; P25/P75: 25th/75th percentile
Source: own calculations based on FADN data; 2) own calculations based on STATISTISCHES BUNDESAMT (2017b) (without permanent crops)

sample characteristics. On average, 18.3 observations per farm are available in the entire income sample (N=1,755). The observations per year vary, because often in the first and last 1-2 years of the period 1996/97-2015/16 less observations are available than in the rest of the period. The average income is 51,043 € per farm.

Other grazing livestock farms are substantially unrepresented in our sample in comparison to the population of German farms, because a large share of the other grazing livestock farms are small and managed by part-time farmers, which are not subject of our study. The same applies to the geographical distribution (Table 3). Due to the exclusion of small farms and part-time farms, farmers are under-represented in the south of Germany (Baden-Württemberg and Bavaria). Further description of the data is provided in Annex 4.

4 Results

In this section, we first display results of different risk formation methods, then present the calculated risk measures for income, prices and yields, and finally describe the results of the income risk decomposition.

Table 3. Share of farms in federal states

Federal state	Share of farms in %	
	Sample (income analysis)[1]	Population of German farms[2]
Baden-Württemberg	10	15
Bavaria	25	33
Brandenburg	3	2
Hamburg	2	<1
Hesse	6	6
Lower Saxony	17	14
Mecklenburg-Vorpommern	3	2
North Rhine-Westphalia	13	12
Rhineland-Palatinate	7	6
Saarland	1	<1
Saxony	3	2
Saxony-Anhalt	4	2
Schleswig-Holstein	5	5
Thuringia	2	1
Total (Germany)	100	100

Source: 1) own calculations based on FADN Data; 2) STATISTISCHES BUNDESAMT (2017b)

4.1 Influence of Expected Value Formation on Risk Measures

Knowing that the expected value is central to quantify risk exposure we test different risk formation methods. The CV and the LPM(30)^0 differ depending on risk formation method (Figure 1). We show the CV and the LPM(30)^0 depending on three expected value formation methods for all farms and differentiated for crop as well as pig & poultry farms.

It is striking that the influence of the risk formation method on both risk measures is systematic: CV's calculated based on the method $trend$ are the lowest and CV's based on the method $adap1$ are the highest. The average CV for crop farms computed with $adap1$ is 35% (=(72.7-53.8)/53.8) higher than the average CV computed by the method $trend$. For pig & poultry and all farms the difference is 30 and 33%. The results of the pairwise statistical hypotheses test and a one-group confidence interval (Annex 5) indicate that differences between trimmed means of each formation methods' CV can also be found in the population of German full-time farmers.

The right part of figure 1 provides an overview of the influence of expected value elicitation method on the assessment of severe events (measured by LPM(30)^0). The influence of the different formation methods $trend$, $adap3$ and $adap1$ on severe events are comparable to the results for CV: $trend$ has the lowest LPM(30)^0 and $adap1$ the highest LPM(30)^0.[13] The average LPM(30)^0 formed by $adap1$ is 20% higher for crop farms, 13% for pig & poultry farms and 19% for all farms of the sample than the average LPM(30)^0 using the method $trend$.

The distribution of both risk measures (but especially CV) of the individual farms is indicated by the box (includes 50% of farms) and whiskers (includes 95% of farms). There are substantial differences between farms of one type (e.g. difference between 2.5th and 97.5th percentile of CV for crop farms is 190%-points) and significant overlaps of boxes and whiskers across periods, farm types and formation methods. Due to these substantial overlapping of the individual evaluation groups, the difference in trimmed means must be put into perspective.

We conclude that the expected value formation method has an influence on the measured level of risk, because absolute values differ between our methods. However, a robust CV and LPM(30)^0 can be formed with $trend$, $adap3$ and $adap1$, because the relative ranking of risk measures calculated with different expected value formation methods hardly vary. We can observe these results for all farm types and prices (see Annex 7 - Annex 10).

Given the generally similar relative ranking of risk measures provided by the different elicitation methods, we concentrate on one approach for expected value formation in the remainder of the paper to improve readability and ease understanding of results. We chose the detrending approach, as this allows to use the full time series of observations, whereas the adaptive expectation methods would imply loosing observations of the already not very long time series of 20 years.

4.2 Risk Measures

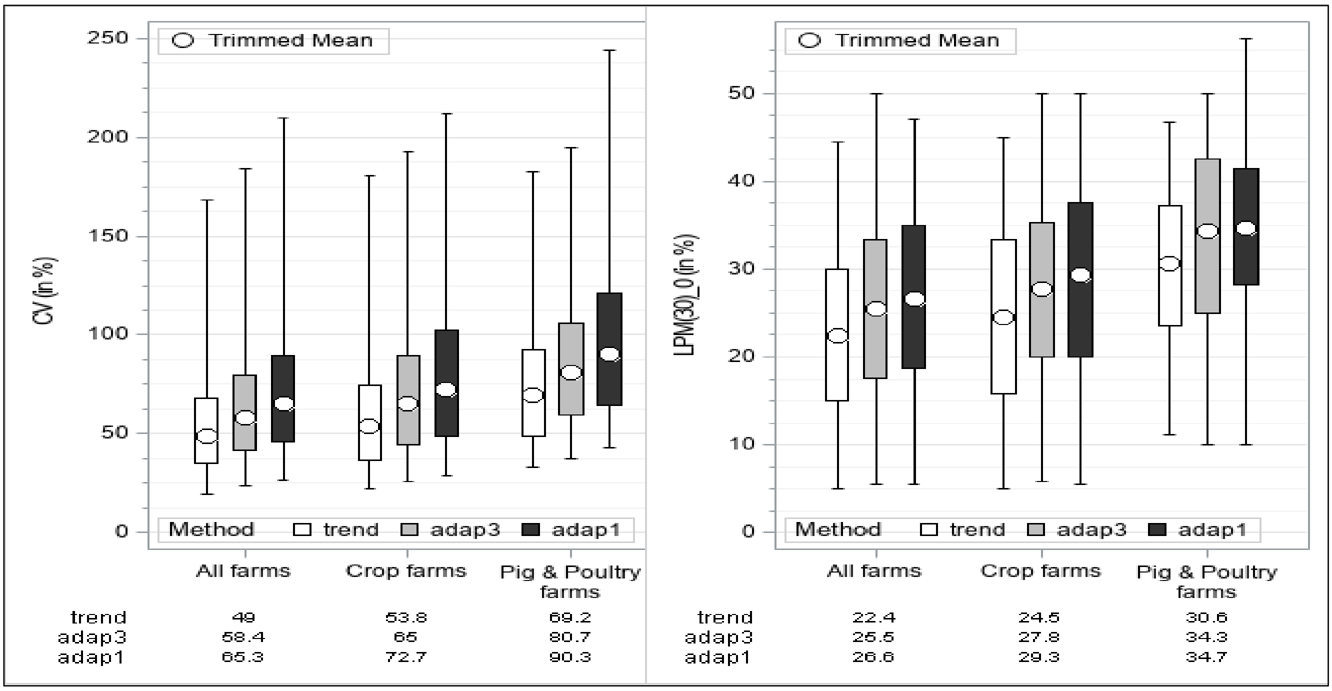
Farm income, price and yield risk are quantified by the CV to measure relative fluctuations and by the LPM(30)^0 to measure the occurrence of severe events.

Income Risk

Figure 2 shows the CV of income of six farm types: crops, horticulture, specialized dairy, other grazing livestock, pig & poultry and mixed farms. The CV on average is 49%, but varies across farm types. The lowest CV is observed for dairy farms (43.1%) and

[13] See confidence intervals in Annex 6.

Figure 1. The impact of different methods for determining the expected value on risk measures: boxplots of implied CV and LPM(30)^0 for farm income



Box: 25^{th} to 75^{th} percentile; whiskers: 2.5^{th} to 97.5^{th} percentile; methods for determining the expected value: trend = based on linear trend; adap1 = adaptive expectation based on previous year; adap3 = adaptive expectation based on three previous years
CV = coefficient of variation; LPM(30)^0 = probability of a negative deviation of more than 30% from the expected value
Source: own calculations based on FADN data

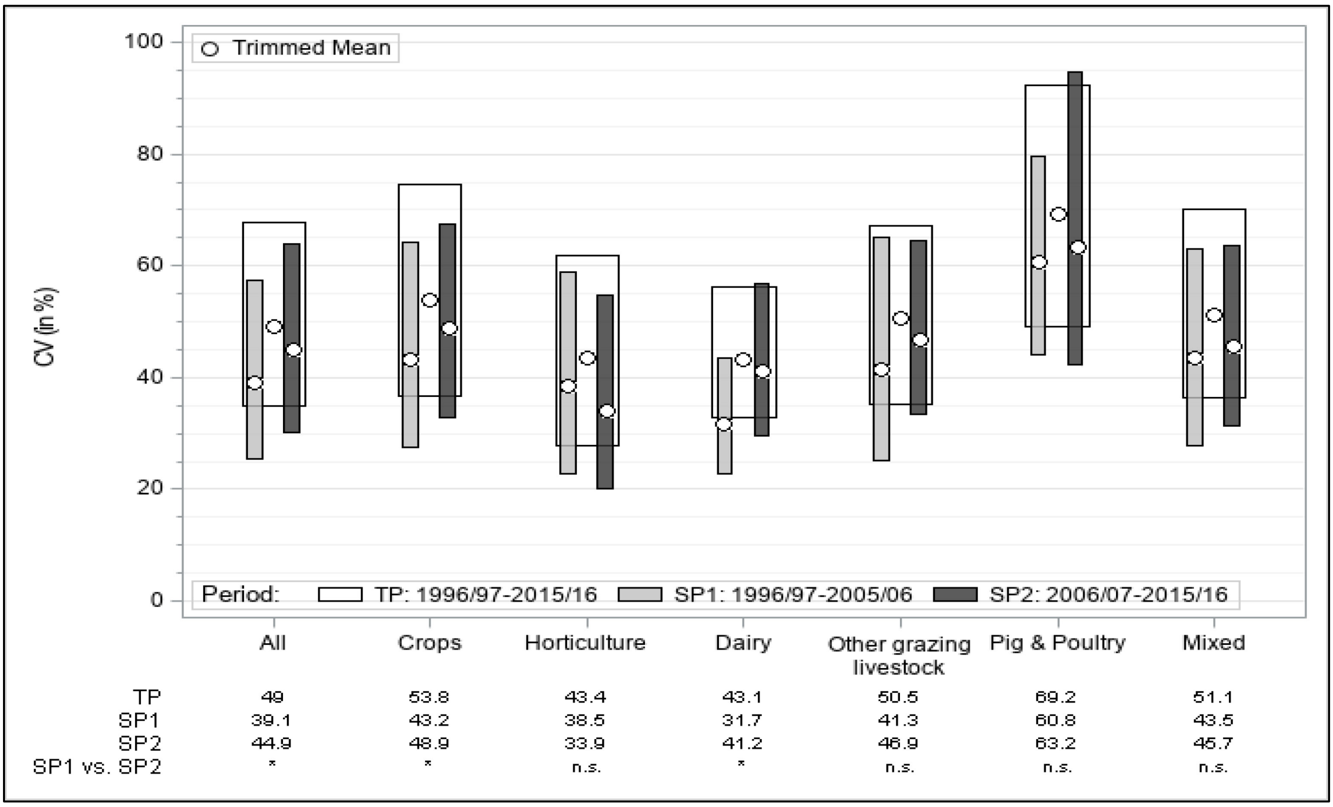
the highest in pig & poultry farms (69.2%). Comparing SP1 and SP2 for all farms we observe on average an increase in the CV by 15%-points. The increase is especially large in in dairy farms (+30%) and crop farms (+13%) (the biggest subsamples). Other grazing livestock and mixed farms show a smaller increase in income fluctuations, while the CV of income in pig & poultry farms remains more or less similar in the two subperiods, and decreases for horticulture farms. Despite differences in the trimmed mean, there is a big overlap of interquartile ranges. Still, a hypothesis test shows that the differences between the trimmed means of the CVs of each farm type can also be found in the population (see Annex 11 and Annex 12[14]). Also, the hypothesis for equality of the trimmed mean in SP1 and the trimmed mean in SP2 can be rejected for crop and dairy farms as well as for the total sample. Further it is striking that the CV in TP exceeds the CV in SP1 and SP2. This is a consequence of the period-specifc detrending of SP1 and SP2 which captures some risk in the subperiods.

The LPM(30)^0 also varies across farm types (Figure 3). The average sample LPM(30)^0 in TP is 22.4%, meaning that on average a farm experiences a severe drop in income almost every fourth year. The lowest risk for severe events in TP is in dairy farming (19.2%) the highest in pig & poultry farming (30.6%). We apply LPM(30)^0 only for TP, because LPM(30)^0 is less robust in short time series of subperiods and severe events are hard to assess in short time series due to their rare character.

We conclude that income risk is heterogeneous. While the farm type explains a part of the level of income risk, there are still significant unexplained differences between farms. The moderate increase of the CV in SP2 for the total sample is mostly due to the strong increase of income risk observed for dairy farms, and, though to a lesser extent, in crop farms. Nevertheless, dairy farms still face low income risk compared to other farm types. Severe events of 30% deviation from the expected value occur on average between every 3rd and 5th year depending on the farm type.

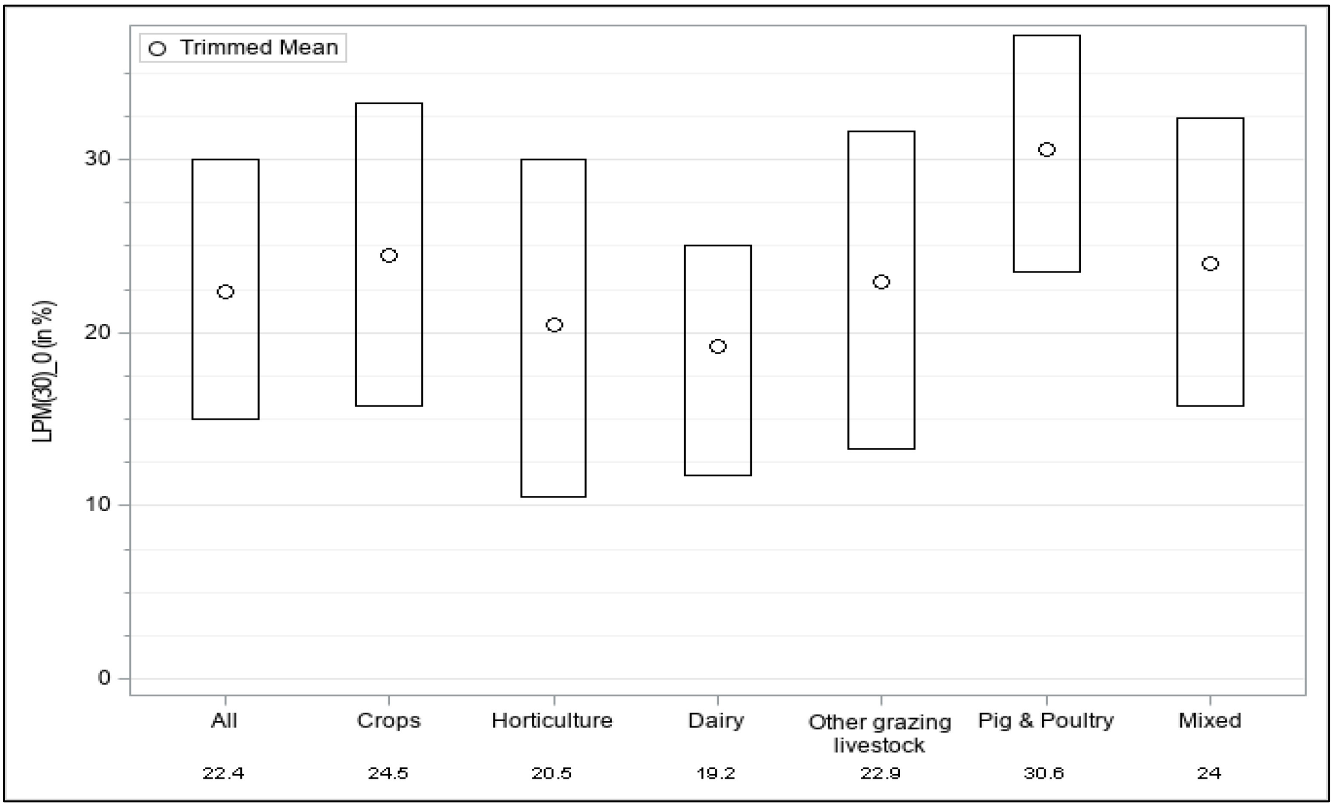
[14] P-values and confidence intervals for the following results of our risk measures can also be found in the Annex.

Figure 2. CV for income depending on farm type and period



Box: 25th to 75th percentile; *(n.s): Hypotheses of SP1 and SP2 being equal (not) rejected at 5%-level; CV = coefficient of variation
Source: own calculations based on FADN data

Figure 3. Probability of severe income drop (LPM(30)^0) depending on farm type during the period 1996/97 – 2015/16



Box: 25th to 75th percentile; LPM(30)^0 = probability of a negative deviation of more than 30% from the expected value
Source: own calculations based on FADN data

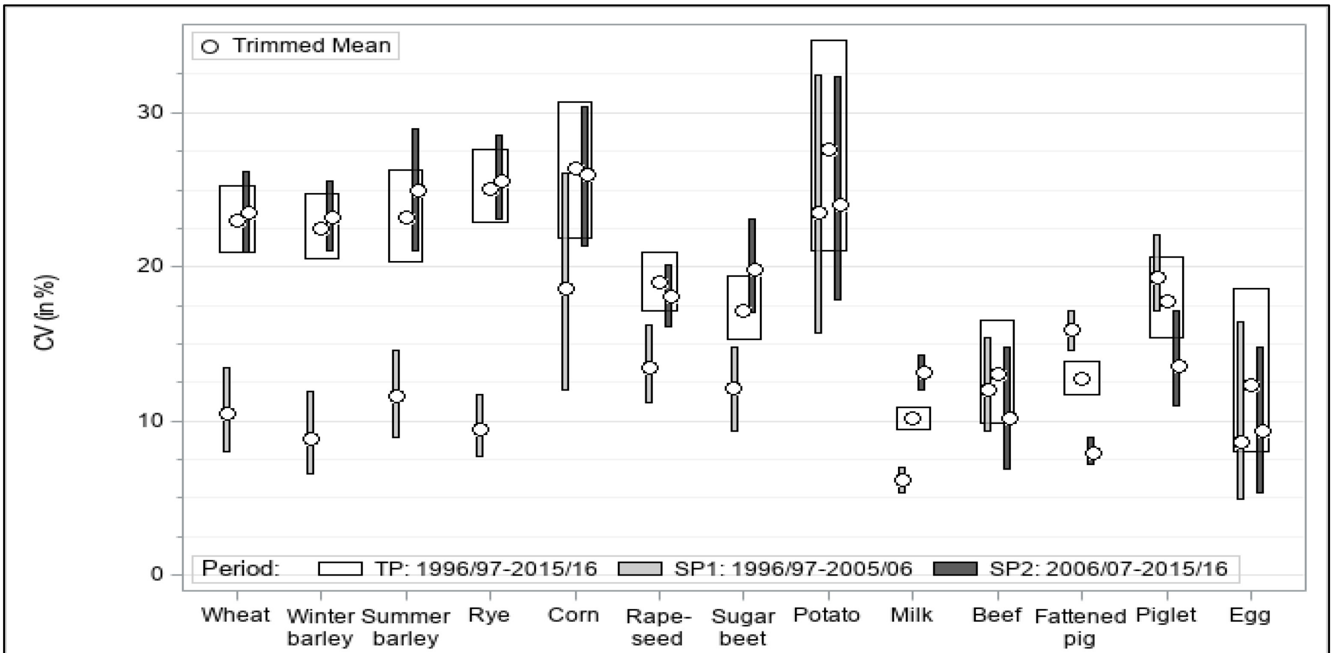
Price Risk

While income risks increase moderately, the analysis of price risk draws a different picture. Figure 4 shows the CV of prices for crops (left hand side) and animals and animal products (right hand sight). We observe higher CVs for crop prices and lower CVs for animal and animal product prices. The lowest CV in TP is 10.2% for milk and the highest is 27.6% for potatoes. Further, indicated by different box lengths, we see that there are little differences in price risk between individual milk producers while there are big differences between potatoes farmers. If we consider changes between SP1 and SP2 we see that there is a substantial increase of price fluctuations for crops (except potatoes), with the highest increase observed for rye (+169%) and milk (+111%). For beef, fattened pig and piglet, fluctuations decreased, especially for fattening pigs (-50%). For methodological purposes it shall be noted that the higher CV in TP in comparison to SP1 and SP2 is due to the subperiod specific trend (when analysing subperiods), which captures some risk (see above). In our analysis of price risk this effect is particularly noticeable as there are strong differences in price developments between SP1 and SP2. The hypothesis of CV's trimmed mean being equal in SP1 and SP2 can be rejected for most products (see Figure 4).

In TP the lowest LPM(30)^0 can be observed for milk and rapeseed (0%) and the highest for potatoes (12.3%) (Figure 5). Results of the LPM(30)^0 differ from the CV. Rapeseed and sugar beet face a relatively low severe event risk compared to other crop products and piglet face a higher severe event risk than other livestock products. Also, for some products we observe differences in the price risk between farms, indicated by the length of the boxes.

For price risk we conclude that differences between products exist, especially between crop (high) and livestock (low) products. Differences also occur between SP1 and SP2. Milk and rapeseed prices do not fall below the -30% threshold and thus do not register any severe events.

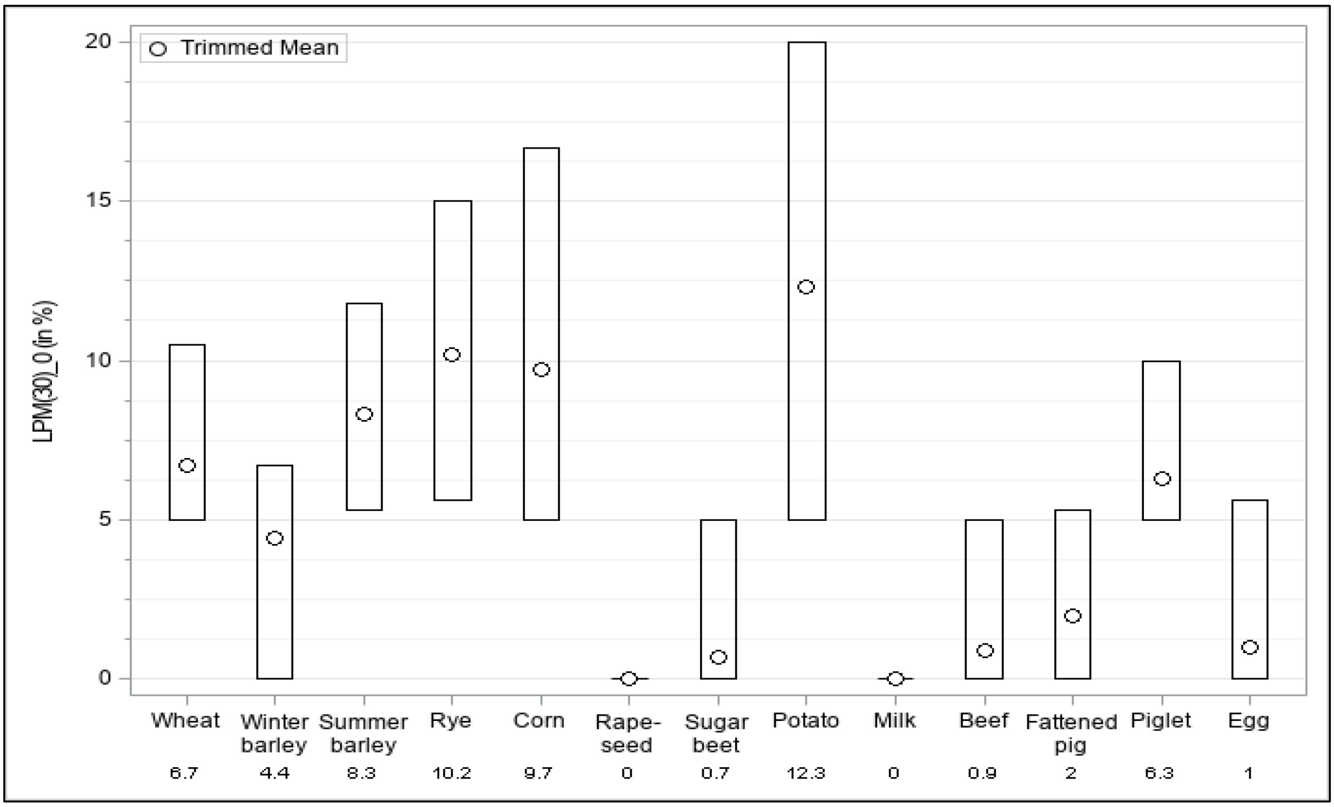
Figure 4. CV for prices depending on product and period



	Wheat	Winter barley	Summer barley	Rye	Corn	Rape-seed	Sugar beet	Potato	Milk	Beef	Fattened pig	Piglet	Egg
TP	23	22.5	23.2	25.1	26.4	19	17.2	27.6	10.2	13	12.7	17.8	12.3
SP1	10.5	8.8	11.6	9.5	18.6	13.5	12.1	23.5	6.2	12	15.9	19.3	8.6
SP2	23.5	23.2	24.9	25.6	26	18.1	19.8	24	13.1	10.2	7.9	13.6	9.4
SP1 vs. SP2	*	*	*	*	*	*	*	n.s.	*	*	*	*	n.s.

Box: 25th to 75th percentile; *(n.s): hypotheses of SP1 and SP2 being equal (not) rejected at 5%-level; CV = coefficient of variation
Source: own calculations based on FADN data

Figure 5. Probability of severe price drop (LPM(30)^0) during the period 1996/97 – 2015/16 depending on product



Box: 25th to 75th percentile; LPM(30)^0 = probability of a negative deviation of more than 30% from the expected value
Source: own calculations based on FADN data

Yield Risk

Finally, we analyse yield risk starting with the CV (Figure 6). In TP the lowest risk is observed for wheat (15%) and the highest for rapeseed (23.1%). The variations between farms are similar across products. Considering the changes over time, we observe a slight increase in the CV for grains (except corn and wheat) and potatoes. For rapeseed we observe a decrease in yield fluctuations. While interquartile ranges overlap, the hypothesis test shows that differences between the trimmed mean CV of SP1 and SP2 can also be found for all crops in the population of German farms (except for corn and potatoes).

The LPM(30)^0 for yields show that lowest percentage of severe yield drops can be observed for wheat (2.5%) and highest for rapeseed (9.5%) (Figure 7). The overall picture of LPM(30)^0 is similar to the CV.

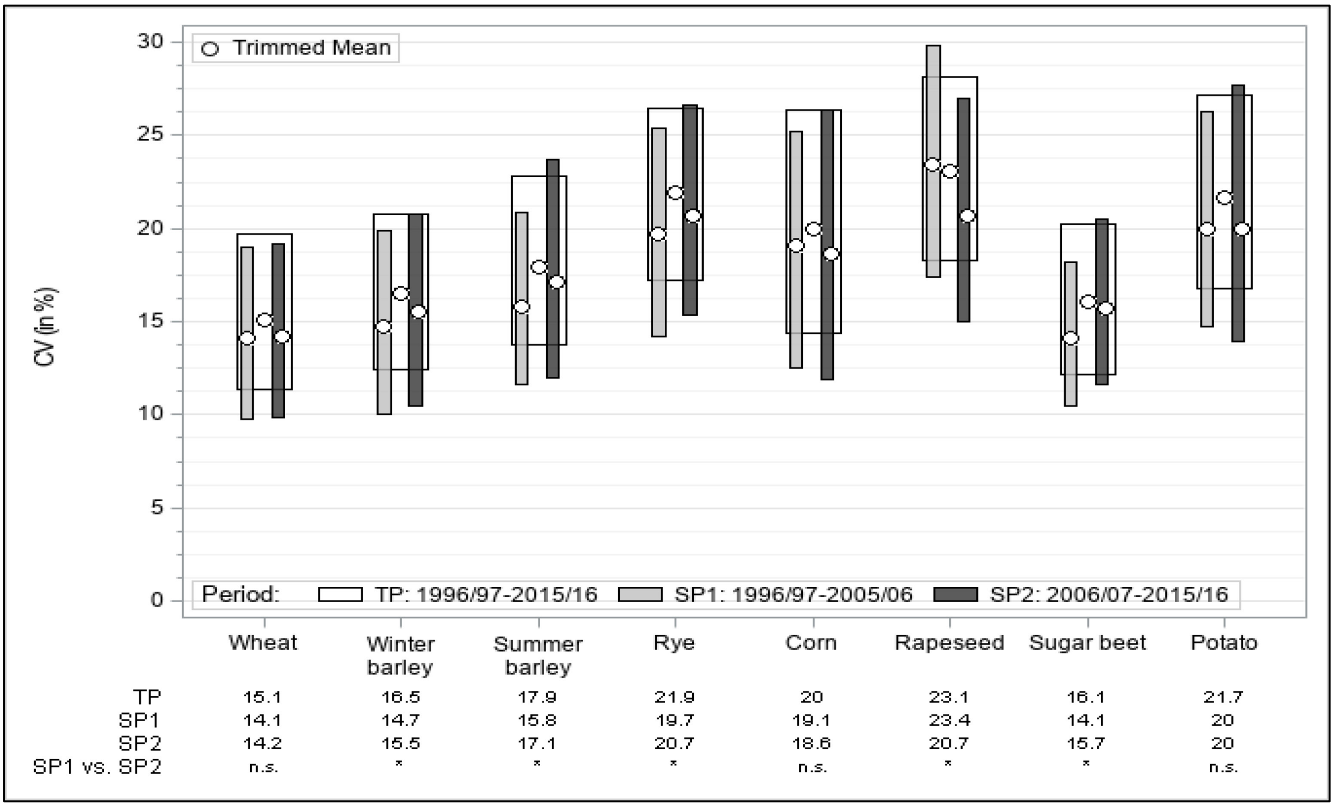
The influence of the region on the yield risk is also relevant. While the CV for rye in Lower Saxony is higher than the CV for wheat, this difference is marginal in Brandenburg (see Annex 20 and Annex 21 for details). Nevertheless, the order of observed CVs does not change.

We conclude for yield risk that it is slightly increasing for most crops. Differences of farms (e.g. region) influence the risk level. In the light of our data yield drops of more than 30% are on average observed every 10th year for rapeseed to every 40th year for wheat.

Summary for Risk Measures

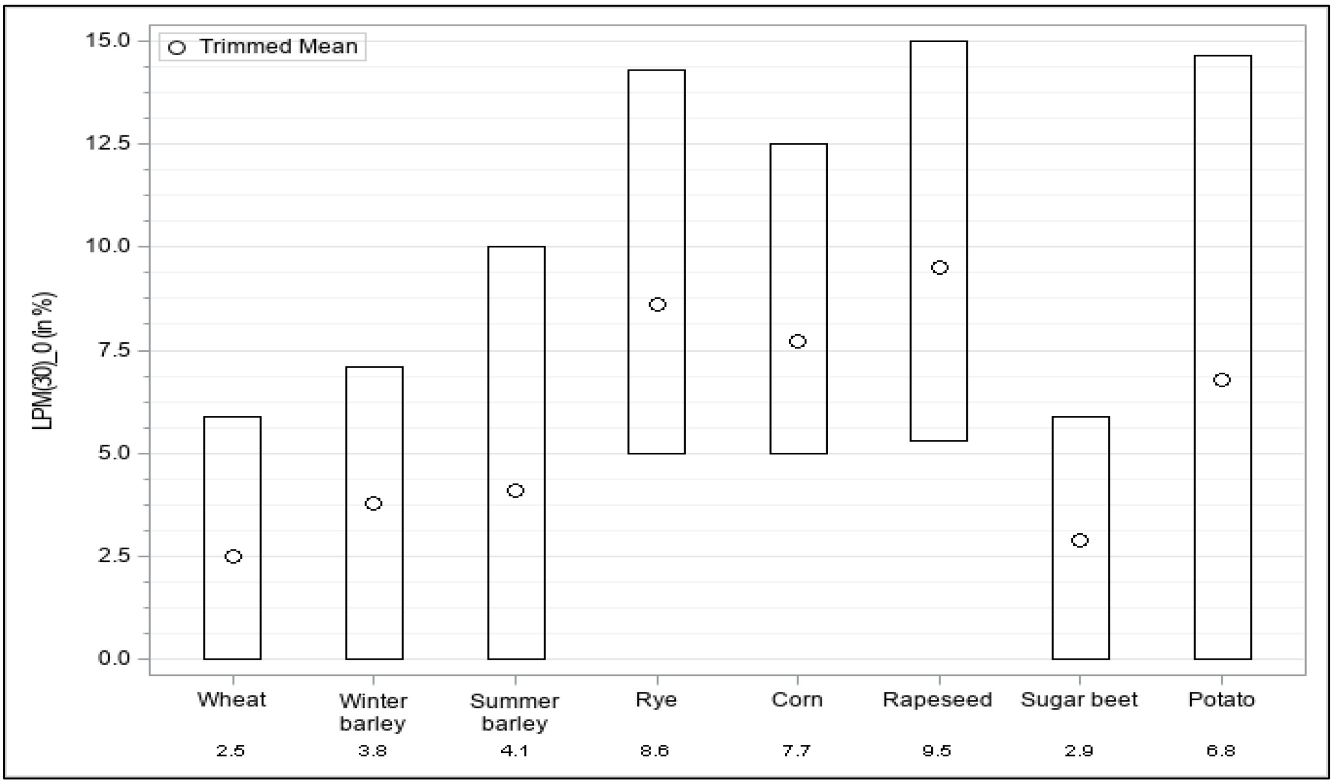
In summary we find that the level of risk faced is heterogeneous across farms. Some variation can be explained by farm types and subperiods. Comparing income risk in SP1 and SP2 we observe an increasing tendency in income risk (particularly for crop and dairy farms). Income risk of dairy farms and milk price risk increased from a low level of risk to a still below-average level of risk for both risk measures (CV and LPM(30)^0). It is striking that level of CV and LPM(30)^0 for income is substantially higher than level of CV and LPM(30)^0 for prices and yields.

Figure 6. CV for yields depending on product and period



Box: 25th to 75th percentile; *(n.s): hypotheses of SP1 and SP2 being equal (not) rejected at 5% level, CV = coefficient of variation
Source: own calculations based on FADN data

Figure 7. Probability of severe yield drop ($LPM(30)^0$) during the period 1996/97 – 2015/16 depending on product



Box: 25th to 75th percentile; $LPM(30)^0$ = probability of a negative deviation of more than 30% from the expected value
Source: own calculations based on FADN data

Table 4. Contribution of income components to the variance of income depending on farm type (in %)

	Direct effect				Interaction effect					
	Sales revenue	Other revenue	Material cost	Other cost	Sales revenue with material cost	Sales revenue with other cost	Sales revenue with other revenue	Material cost with other revenue	Material cost with other cost	Other revenue with other cost
All	109 ↑*	38 ↘*	28 ↗*	36 ↘*	-63 ↓*	-34 →	2 ↗*	-6 ↘*	11 ↗*	-22 ↗*
Crops	105 ↑*	36 ↓*	16 ↗*	32 ↘*	-43 ↘*	-31 ↗*	2 ↗	-5 ↘	7 ↘	-20 ↗*
Horticulture	138 ↗	30 ↘*	43 ↗	74 ↓*	-94 ↘	-77 →	5 →	-5 ↗	20 ↗	-35 ↑*
Dairy	99 ↑*	39 ↓*	23 ↗	41 ↘*	-54 ↓*	-33 ↘	2 ↗*	-5 ↘*	12 ↗*	-24 ↗*
Other grazing livestock	110 ↗	63 ↘*	44 ↗	32 ↗	-79 ↘	-23 ↘	-28 ↑*	-6 ↘	13 →	-25 ↘
Pig & Poultry	175 ↗	30 ↗*	79 ↑*	17 ↗	-163 ↓*	-31 ↗	2 ↘	-15 ↘*	18 ↗	-12 →
Mixed	134 ↑*	43 ↘*	47 ↗*	32 ↘	-109 ↓*	-37 ↘	6 ↗	-14 ↘	17 ↗	-20 ↗*

Arrows indicate change between SP1 (1996/97-2005/06) and SP2 (2006/07-2015/16); vertical arrow: >30 percent-points change; sloping arrow: 30 to 0 percent points change; horizontal arrow: 0 percent points change; *: null hypothesis of trimmed mean for SP1 and SP2 being equal is rejected at 5%-level.
Source: own calculations based on FADN data

4.3 Income Risk Decomposition

First, income risk variation is decomposed into its components sales revenue, other revenue, material costs and other costs.[15] Second, variance of revenue is decomposed into price and yield variance. Finally, we quantify the contribution of all components to severe income drops.

Decomposition of Income Variation into Revenue and Cost Components

The results of the income variance decomposition (Table 4) show that the contribution of sales revenue is higher than that of other direct effects and thus the most important component in the period 1996/97-2015/16 (109% for all farms). The lowest contribution of sales revenue is observed for dairy farms (99%), the highest for pig & poultry farms (175%). Importance of other revenue, material costs and other costs is generally lower and depends on the farm type. Outstanding are the high contributions of the direct effect of other costs in horticulture (e.g. labor costs) and the direct variance effect of material costs in pig & poultry farms (e.g. feed).

For every farm type in all periods (except for crop and dairy farms in SP1) the contribution of sales revenue fluctuations to income variance is above 100%. The occurrence of values larger than 100% for the contribution of one direct effect (or even for the sum of all direct effects) may be surprising at first glance. The reason is that the sum of all direct **and** interaction effects is defined to be 100%[16]. Interaction effects, which are based on the correlation between two components, can reduce overall income risk (i.e. have a 'negative' contribution to overall variance), thus implying that some components' contribution is above 100%. For instance, the direct effect of sales revenue variation on income variation (109%) is reduced by its interaction with material cost (-63%), which means that in years with low (high) sales revenue also low (high) costs can be expected. In TP the most negative interaction (highest variance reduction) is observed for material costs in pig & poultry farms (-163%). Also, interactions between sales revenue and material costs in horticulture, other grazing livestock, and mixed farms are high (-109 to -79%), as well as the interaction between sales revenue and other costs in horticulture farms (-77%). A positive contribution of the interaction term to income variance is rarely observed (highest value: +20% for material costs and other costs in horticulture). It is striking that interaction terms for crop and dairy farms are rather low compared to other farm types.

[15] To simplify the decomposition analysis, financial income, extraordinary income, taxes on income and earnings as well as other taxes are excluded from our decomposition analysis because preliminary results showed that these factors are off minor importance for variation of our income metric, even though they are components of income. See Annex 2 for details of calculating risk components.

[16] While the sum is 100% for each individual farm, for aggregated group data the sum sometimes differs from 100% because the aggregation is based on the trimmed mean rather than the arithmetic mean. For Table 4 and 5, the values were therefore scaled to sum up to exactly 100%.

Looking at changes between SP1 (1996/97-2005/06) and SP2 (2006/07-2015/16), indicated by arrows in Table 4, we see that the importance of sales revenue fluctuations for income risk increases in the second period, the importance of material costs decreases (except in pig & poultry farms) and the interaction effect between sales revenue and material costs becomes stronger (more negative). However, findings regarding differences between periods show big overlaps of interquartile ranges (see Annex 22), which shows that the importance of single components varies across farms and may overlay differences between periods. Nevertheless, a hypothesis test shows that the difference between the trimmed means of SP1 and SP2 can also be observed for most farm types and risk components in the population of German farms.

Decomposition of Revenue Variation into Price and Yield Components

Table 5 shows the decomposition of crop revenue into the direct price and yield effect as well as the interaction effect of price and yield. The direct price and yield effect add up to more than 100% due to their negative correlation which reduces revenue risk (price times yield). Further Table 5 illustrates, that price variation has a higher contribution to revenue variation than yield variation (for every crop except rapeseed). The lowest contribution of price variations to the variance of revenues can be found for the direct effect of rapeseed (52%), the highest for sugar beet (90%). For yields the lowest contribution is observed for wheat (38%) and the highest for rapeseed (74%). All interaction terms are significantly negative (except for summer barley). This means that on average a positive deviation of prices can be expected, if yields decline. We observe the weakest interaction (-1%) for summer barley, as summer barley is largely produced and marketed as malting barley under special conditions. The highest (most negative) interaction between yields and prices can be found for sugar beet being -62%. The reason for this is that the EU sugar beet market was strongly protected by export quotas and import duties until 2017, and therefore an oversupply or undersupply of sugar beet on the EU market had a major influence on domestic price development. The decreasing interaction effect for sugar beet in SP2 can be explained by the fact that the EU sugar market regulation was reformed in 2005 (ZEDDIES, 2006). Comparing SP1 and SP2 we find that the importance of price variation for revenue variance increased. In SP1 yield risk is dominating for all crops except potatoes, while in SP2 price risk is dominating for all crop products except rapeseed (see Annex 23 for details). The hypothesis test shows that the difference between the trimmed means of SP1 and SP2 can also be observed for all crops in the population of German farms (except potatoes). Annex 23 shows 25th and 75th percentiles of our results.

Table 5. Contribution of price and yield variance to the variance of revenue (in %)

	Direct effect				Interaction effect	
	Price		Yield		Price with yield	
Wheat	81	↑*	38	↓*	-19	↘*
Winter barley	73	↑*	48	↘*	-22	↓*
Summer barley	61	↑*	39	↘*	-1	↘*
Rye	74	↑*	55	↓*	-29	↘*
Corn	69	↗	44	↓*	-13	↑*
Rapeseed	52	↑*	74	↘*	-29	↘*
Sugar beet	90	↓*	72	↓*	-62	↑*
Potato	85	↗	56	↘	-38	↗

Arrows indicate change between SP1 (1996/97-2005/06) and SP2 (2006/07-2015/16); vertical arrow: >30 percent-points change; sloping arrow: 30 to 0 percent points change; horizontal arrow: 0 percent points change; *: null hypothesis of trimmed mean for SP1 and SP2 being equal is rejected at 5%-level.
Source: own calculations based on FADN data

Contribution of Severe Declines in Single Risk Components to Severe Income Declines

Finally, we quantify the contribution of severe declines in the risk components (event B) to the occurrence of severe income declines (event A). To this end, we count observations for every farm and aggregate them for the sample (Table 6). Our whole sample has 32,135 observations (1,755 farms * 18.3 observations per farm). Severe declines in farm income (event A) occur 7,255 times (7,255/32,135*100%≈22%). For B = "severe drop in sales revenue" the frequency of severe income declines is 745 (2%). A severe income decline and a severe sales revenue decline at the same time on one farm occur 472 times (1%). In addi-

Table 6. Observed frequency of severe income declines and severe sales revenue declines over all farm types and years

	Severe income decline	No severe income decline	Total
Severe sales revenue decline	472	273	745
No severe sales revenue decline	6,783	2,4607	31,390
Total	7,255	2,4880	32,135

Source: own calculations based on FADN data

tion, we see that in 472 of all 745 cases of severe sales revenue declines (472/745≈ 63%) a severe income decline occurs, which also means that in 243 cases of severe sales revenue declines (37%) a severe income decline does not occur. In other words, this means that a farm which experiences a decline of more than 30% in sales revenue has a 63% probability of experiencing an income drop of more than 30%.

We conclude that while a 30% drop below the expected income happens quite often, a drop of 30% in sales revenue is rare and a combination of 30% drop in income and 30% drop in sales revenue is even rarer. However, if a drop of at least 30% for sales revenue does occur, then the probability of a 30% drop of income increases substantially.

Table 7 illustrates the observed probabilities of a severe decline of income P(A) and different risk components P(B), as well as the probability of severe decline of income and risk component at the same time P(A∩B) and the conditional probability of a severe income decline if a severe component decline already occurred P(A|B). Results are differentiated for sales revenue, other revenue, material costs and other costs as well as farm types. In addition, we consider the impact of yield and price declines of the crop with the highest relative scope of cultivation as well as the impact of milk price declines.

The results show that the probability for severe income drops range between 19% (dairy) and 31% (pig & poultry). Probabilities for severe drops in risk

Table 7. Contribution of severe declines in components to severe income declines (in %) during the period 1996/97-2015/16 depending on farm type

Farm type	Probability of severe income declines in % "P(A)"	Component	Probability of severe component decline in % "P(B)"	Probability of severe component and severe income decline in % "P(A∩B)"	Probability of severe component decline if a severe income decline occurred in % "P(A|B)"
All	22	Sales revenue	2	1	63
		Other revenue	7	3	42
		Material costs	3	< 1	27
		Other costs	6	3	45
Crops	25	Price[1]	7	3	48
		Yield[1]	4	2	45
		Sales revenue	4	3	68
		Other revenue	5	2	50
		Material costs	4	1	27
		Other costs	8	3	39
Horti-culture	21	Sales revenue	2	< 1	46
		Other revenue	13	4	30
		Material costs	4	1	25
		Other costs	6	2	37
Dairy	19	Milk price	0	0	N.A.
		Sales revenue	1	< 1	62
		Other revenue	7	3	41
		Material costs	3	< 1	28
		Other costs	6	3	48
Other grazing livestock	23	Sales revenue	5	2	45
		Other revenue	7	3	42
		Material costs	5	1	28
		Other costs	5	3	57
Pig & Poultry	31	Sales revenue	3	2	76
		Other revenue	12	6	47
		Material costs	3	1	32
		Other costs	6	3	53
Mixed	24	Sales revenue	2	1	64
		Other revenue	6	3	46
		Material costs	2	< 1	26
		Other costs	5	3	51

1) Price and yield of the crop with highest scale of cultivation (in terms of area)
Source: own calculations based on FADN data

components are far lower and ranging between 0% (e.g. milk prices) and 13% (for other revenue in pig and poultry). The occurrence of both a severe income drop (event A) and a severe drop of a risk component (event B) in one year is even more rare (between 0% for the milk price and 6% for other revenue in pig & poultry). However, for all risk components (except the milk price) the probability for a severe income drop increases if a severe decline of a risk component already occurred (25% for material costs in horticulture to 76% for sales revenue for pig & poultry farms). The price of milk has not fallen below the threshold of -30% for a single farm.

The results on the importance of the severe declines in risk components for observed severe income declines can be interpreted differently depending on the perspective. On the one hand, hedging against single risk components will reduce the probability of a contemporaneous occurrence of a severe income decline, even if only for a share of the severe income declines. On the other hand, a severe decline in a risk component, for instance yield, is inadequate to indicate a severe decline in farm income. In 50% of the cases, the degree of affectedness would not be correctly predicted. Even for severe declining sales revenues, in which price *and* yield declines are included, the observed importance of the conditional probability for a severe income decline is not very high (only 63% probability) and thus severe sales revenue declines by far do not effect in every case a severe income decline.

We conclude that sales revenue for all farm types is the most important reason for severe declines in income. Next, declines of other revenue are important. Strong surges of material costs and other costs are, compared to revenue, less important for severe declines in income. However, all risk components contribute to or trigger severe income declines.

Summary for Income Risk Decomposition

We summarise that severe declines in the risk components increase the likelihood of severe declines in income. Nevertheless, a severe decrease in a risk component does not necessarily lead to a severe decrease in income (often, in less than 50% of cases). Overall, for all farm types, the sales revenue is of highest importance for severe declines in income. In addition, it is striking that the variance of income is more influenced by price fluctuations than by yield fluctuations, but that for severe income declines yields and prices are of similar importance.

5 Discussion and Conclusion

A comprehensive whole farm risk analysis is the basis for effective risk management of all actors in agriculture. The existing literature is often limited to a single risk component or product group for a limited period of time. This study aims to fill this gap and provides the most comprehensive and up-to date analyses of risk exposition of German farms available, covering a wide range of products, farm types and income risk components, based on long time-series (1996/97-2015/16) data for a large sample of farms. Further, the change in risk exposure before and after 2007 is presented. Also, we examine the occurrence of severe events as these are of specific importance for risk management in agriculture. The quantification of the risk is often based on the calculation of the deviation of a variable from its expected value, which is why the expected value is of central importance for the risk exposure. Our study is one of the few empirical risk studies which explicitly addresses the influence of expectation formation modelling on the measurement of farm income risk.

Our results show that the risk exposure of German farmers is very heterogeneous (corroborating the findings of EUROPEAN COMMISSION, 2017b; KIMURA et al., 2010, and SEVERINI et al., 2019). This is due to two reasons. First, individual income risk is subject to different environmental conditions (e.g. climate, soil, market) which result in different risk levels and thus cause heterogeneity. Second, the composition of various risk components varies and thus causes heterogeneity. Accordingly, risk management is a complex task that has to be carried out on an individual farm basis.

By using the CV (for quantifying the extent of relative variations) and the $LPM(30)^0$ (for quantifying the occurrence of severe events), our risk measurement shows that the perceived levels of risk (in public, in the media) do not reflect the level of risk present in the data. The objective measurement of the risk helps to assess risk realistically. Our analysis reveals an overall increase in income risk; however, the development of risk is ambiguous depending on the type of farm, which differs from the results HANF and CORDTS (1983) found for the period 1968/69-1979/80. The substantial increase in price risk from 2007 onwards does not increase farm income risk to the same extent. Despite the increase in the income risk for dairy farms, the level of risk in dairy farming is comparatively low even in the more recent time period analysed. In contrast, the income risk for pig & poultry farms is the highest. This is a result also established by EUROPEAN COMMISSION (2017b) for other EU member states. A comparison of the results on severe income declines to those reported in the literature on income stabilisation is often made difficult by the use of different income measures, which has a strong impact on the share of affected farms. Based on a similar income measure, EL BENNI et al. (2016) report an average annual frequency of 14% for severe income declines in Switzerland for the period 2006 to 2009. SEVERINI et al. (2019) observe an annual average frequency of 21% for severe income declines in Italy for the period 2011 to 2014. The latter study comes to a similar result as our study, which is an average annual frequency of 22% for severe declines. The differences between farm types concerning the likelihood of severe income declines are often found to be like those of our study, with specialised granivore livestock farms having the highest share of affected farms and mixed farms being least affected. (SEVERINI et al., 2019; DELL'AQUILA and CIMINO, 2012; EUROPEAN COMMISSION, 2017b). The widespread perception of an economic crises triggered by price fluctuations in dairy farming despite farm income risk still being lower than that of most other farm types highlights that the change in risk exposure (i.e., the observed increase in price and farm income risk in dairy farming after 2007) can be more relevant than the absolute level of risk. In such situations characterized by changes in risk exposure there is particular potential for farmers to learn from risk management strategies implemented in other sectors that have been exposed to the higher level of risk before.

These changes in risk levels of prices and yields also change the risk structure of farms, as our decomposition of income risk shows. For instance, price fluctuations of arable crops exceed that of yield fluctuations after 2007. The most important (but not the only) driver for both income fluctuations and severe events is sales revenue. Of particular importance are product price fluctuations, as confirmed by the perception of farmers, even if they overestimate them (MÖLLMANN et al., 2018). Since the income risk (especially severe events) is attributable to a large number of factors, the isolated measurement of partial risks like yield risk conveys limited insight into overall risk. While severe events are of particular relevance for risk management, no other studies are known that adequately quantify the causative risk components of severe events. For instance, EUROPEAN COMMISSION (2017b) examines the influence of revenue related severe events on the income, but the correlation with other risk components is not taken into account in the study.

Several policy implications are derived from the risk quantification. First, we conclude that due to the heterogeneity of farms, efficient risk management strategies must be designed and implemented at the farm-individual level. Next, due to the complexity of the agricultural income risk, i.e. numerous individual characteristics of the risk components, their interactions as well as biases present in the perception and management of risks (KAHNEMAN, 2011), it can be assumed that appropriate risk management know-how is required for the perception of risks, i.e. probabilities and damage potentials, as well as for the implementation of efficient risk management measures. Education and consultancy are therefore particularly suitable instruments for promoting risk management. In addition, it is important to use and promote the exchange between the sectors in order to pass on experience in dealing with certain risks. Last, politics should not use a risk component as a single indicator for the economic affectedness of the farm due to a severe event; for instance, a severe decline in yields or prices forecasts income affectedness insufficiently, as generally in less than 50% of the cases these severe events occur contemporaneously with a severe income decline.

Finally, our results show that the formation of the expected value has an influence on the absolute level of risk and thus confirm the theoretical considerations of JUST and RAUSSER (2002) and NERLOVE and BESSLER (2001). Given that the method to form the expected value differs by individuals, the abovementioned heterogeneity in risk exposure is reinforced. How is it possible, although expected values differ from one individual to another, to objectively quantify the risk for each farmer? We propose two possibilities. First, if the absolute risk is to be quantified for a large population of farms, different methods of expectation value formation should be used in parallel. Second, if a study is restricted to only one expected value method, this particular method and its possible effects on the expected value should be stated. Therefore, we recommend that in any study quantifying the risk, the results should be explicitly interpreted in relation to the expected value formation method used. For the farmer and other risk management actors, our result regarding the influence of the expected value formation method also means that the risk can be reduced by more precise expectation value formation. Support in the form of easier, more cost-effective information procurement helps to create more precise expected values (JUST and RAUSSER, 2002). Despite the clear absolute differences between the methods of expectation value formation, the relative differences are independent of the method of expectation value formation.

When making conclusions from our study one has to have in mind that we illustrate the realized (observed) risk on the farm-level. The analysis of observed variability is subject to the usual caveat that some farmers' decisions and strategies (e.g. insurance, financial reserves, private assets, adopted production methods, price hedging) are already embedded in our results (KIMURA et al., 2010). Realised incomes, prices and yields are the result of many factors, such as farm specific (e.g. risk attitude) or external factors (e.g. availability the of insurance, marketing contracts, contracts for price hedging or non-agricultural income in the region as well as regional weather conditions). Thus, risk might differ due to reasons which are not directly rooted in the production system of a farm type or characteristics of a product.

Although our database allows for a comprehensive farm risk analysis it has some shortcomings. First, valid household income data are not included in FADN, although this is often important for decisions in agricultural risk management. We have tried to minimise the impact of off-farm income by analysing the income of only full-time farms with a minimum income-level. At the same time, the exclusion of part-time farms leads to an underrepresents agricultural holdings in southern Germany. Second, the FADN underrepresents complex corporate structures, i.e. economically linked but legally separate entities. This problem primarily affects larger farms and pig & poultry farms (FORSTNER and ZAVYALOVA, 2017). Next, legal persons are excluded from income analysis. In summary, our income analysis thus focuses on the "classical" full-time family farm. For the interpretation of the results on income risk, it thus needs to be taken into account that in regions with a high share of part-time-farms (e.g. southern Germany) or legal persons (eastern Germany) a significant part of agriculture is not represented by the sample. Finally, although farm data of 20 years is much in terms of farm studies, for probability theory 20 years is not much. Especially observations of extreme events in the sampling period could be biased, which does not allow to transfer our results to other (future) periods.

Future research should examine further farm characteristics that explain the risk exposure of German farms. Such characteristics could be, for example, farm size, education level or the use of external production factors. Furthermore, the expected value formation in German agriculture should be empirically investigated. Further methods of expectation formation could be used to describe the absolute level of risk in more detail. Accounting for the role of autocorrelation and cycles in expectation formation and measurement of risk exposure remains a challenge in many empirical settings and merits further research. Also, in our paper, we compare the risk levels specifically for the period before 2007 and the period after 2007. An alternative to splitting the sample would be to use the regression residuals around the trend to estimate income risk and changes over time therein (FINGER, 2010a).[17] This would be an interesting avenue for further research allowing a more data-based identification of the time, speed and type of changes.

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Acknowledgement

We would like to thank Prof. Oliver Mußhoff, who commented on an earlier version of this paper, and two anonymous reviewers for their helpful comments and suggestions.

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