Farm size, environmental risk and risk preferences: the case of Namibian commercial cattle farming

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Abstract: Utilizing a data set of 399 Namibian commercial cattle farmers, we investigate the relations between inter-annual variability in rainfall (environmental risk), risk preferences and farm size. We test several hypothesis from the literature regarding self-selection according to risk preferences and optimal farm management. We demonstrate that the Pareto distribution – which separates the distribution into two parts – is a statistically plausible description of the empirical farm size distribution when 'farm size' is operationalized by herd size, but not by rangeland area. A group comparison based on the two parts of the Pareto distribution shows that larger farms are on average exposed to significantly lower environmental risk than smaller farms. Regarding risk preferences, we do not find any significant differences in mean risk attitude between the two branches. Concerning the overall appearance of the size distribution, we find that a risk-loving attitude comes with more inequality in the distribution of herd sizes among farms. Moreover, our analysis provides evidence for the role of the stocking rate as key parameter in farm management when large environmental risk is present.

JEL Classification: D22, Q12, Q56, R11, R12

Keywords: risk preferences, environmental risk, semi-arid rangelands, cattle farming, stocking rate, farm size, Pareto distribution, range management

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1 Introduction

One third of our planet's land surface is covered by semi-arid regions. Central climatic characteristic of these regions is low precipitation combined with a high inter-annual variability in rainfall. The predominant land use in semi-arid regions is livestock farming, which seems to be the only economically sensible use for these areas (Quaas et al. 2007), and therefore often provides the only livelihood for the local populations. What is more, significant parts of the world's commercial livestock farming also take place in these regions (Millennium Ecosystem Assessment 2005). Grazed semi-arid rangelands are tightly coupled ecological-economic systems (Perrings and Walker 1997, Janssen, Anderies and Walker 2004, Olbrich, Quaas and Baumgärtner 2009) as precipitation levels directly influence the farmer's income, because they determine the amount of forage available for livestock farming. Consequently, precipitation variation may be seen as main income risk to the farmer (Rodriguez1 and Taylor 1988, Quaas et al. 2007, Olbrich, Quaas and Baumgärtner 2009). One can thus treat the coefficient of variation[1] (C_v) of inter-annual precipitation at a specific farm location as a proxy for environmental risk at that location.

Precipitation data is often available from official local and national meteo offices and where it is not, there are reliable methods to generate such data based on calibrated regional climate models (e.g. Jacob and Podzun 1997). In contrast, it is considerably harder to obtain high resolution commercial livestock farming data. If data policy allows at all, national statistics offices can usually only provide classified and anonymized data which does not allow for any detailed analysis of the relationship of farm sizes and environmental risk. Consequently, empirical studies on the relationship of environmental risk and commercial livestock farms in semi-arid regions are, to the best of our knowledge, largely missing from the literature.

The major contribution of the present paper is to provide a detailed empirical analysis of the interrelationships of farm size, stocking rates, environmental risk and the farmer's risk preferences using a unique and highly-detailed 2008 data set of 399 Namibian commercial cattle farmers (Olbrich, Quaas and Baumgärtner 2009, 2012). Furthermore, we will

[1]The coefficient of variation of a series of numbers is defined as ratio of standard deviation σ and mean μ of the series: $C_v = \frac{\sigma}{\mu}$.

be able to provide empirical tests of theories that have been put forward in the literature on semi-arid rangeland management over the years. Extensive commercial cattle farming in Namibia takes place almost exclusively in semi-arid regions (Olbrich 2012) and these regions are among the most variable in terms of inter-annual precipitation levels worldwide (Figure 1). Therefore, Namibian cattle farming provides a prime study subject for our case study. We tackle the following key questions: (1) What is the correlation between farm size and environmental risk, (2) Are there significant differences between different subgroups of farmers (risk-loving compared to risk-averse and 'small' compared to 'large') regarding these correlations, (3) Are there significant differences in mean values of key variables when comparing these subgroups and (4) How are the farmer's risk preferences and inequality of the farm size distribution interrelated?

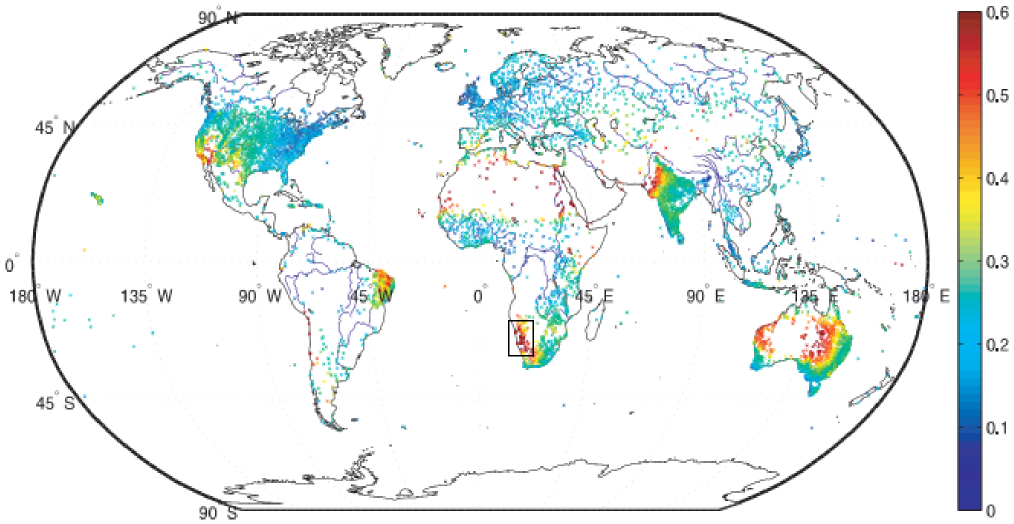


Figure 1: The global map of inter-annual variation of precipitation (Namibia highlighted), re-printed from Fatichi, Ivanov and Caporali (2012).

Methodologically, we use an innovative twist to distinguish between 'small' and 'large' farms: we employ fits of the Pareto distribution (Pareto 1895). The Pareto distribution is widely used for description of wealth and income in economics (cf. Engler and Baumgärtner 2015), and a wide variety of natural phenomena (Sornette 2003, Clauset, Shalizi and Newman 2009). For our purposes, it seems like a natural approach for the following reasons: (1) It has economic microfoundation (Champernowne 1953, Mandelbrot 1961) in a sense that these models treat incomes as stochastic processes, i.e. their evolution over time has a random component. Because of the characteristics of the ecological-economic system laid out above and the hypothesis that farm size is a proxy for wealth (Olbrich, Quaas and Baumgärtner 2009), this formal incorporation of randomness is a very good fit; (2) It contains a parameter, the cutoff value $x_{\min}$, that yields a non-random division of the data set into two parts. It is a longstanding and often implicit hypothesis in the literature that economic entities described by the Pareto distribution (i.e. $x \geq x_{\min}$) are different from the rest, or special in some way (e.g. Auerbach 1913, Champernowne 1953, Mandelbrot 1961). One of our questions here is thus whether we find any evidence for this hypothesis in our sample (see research questions (2) and (3) above).

Our paper is organized as follows. In Section 2, we provide a condensed overview on commercial cattle farming in Namibia. Section 3 describes the data set and its key variables as well as a short description of the Pareto distribution. In Section 4, we present our results before we discuss them in Section 5. Section 6 conludes and gives a brief outlook.

2 Namibian commercial cattle farming

In the following condensed description of the commercial cattle farming sector in Namibia, we follow Olbrich (2012). Commercial cattle farming contributes 37% to Namibia's agricultural output and approximately 1–2% to its GDP. Consequently, farmlands cover close to one fifth of the country's surface and cattle is farmed extensively. There are an estimated 2'500 commercial cattle farmers that typically run their farm in one of the following three production systems: (1) rearing of calves resulting from on-farm reproduction up to the age of eight months before selling them as so-called 'weaners' at auctions; (2) Further rearing of weaners to ages between 18 and 24 months with subsequent sale to the slaughterhouse (as oxen) and (3) buying weaners at the age of eight months and raising them for about 10 to 16 months before selling them to the slaughterhouse. Auctions take place frequently all over Namibia. Although, of course, output prices may vary over time, this risk is spread homogenously over the farmers since there are practically monopsonies in the Namibian market: almost all oxen are purchased by MeatCo of Namibia and almost all weaners sold at auctions go to a very limited number of South African buyers which are feedlot corporations.

In extensive cattle farming, the sheer area of farmland is absolutely crucial. Because Namibia's commercial cattle farming takes place in its semi-arid regions almost exclusively, precipitation risk (i.e. the inter-annual variation of precipitation), which is effectively a 'grass production risk' (cf. Obrich 2012: 23), is by far the most prominent income risk to the farmer (Quaas et al. 2007). Moreover, due to the lack of sufficient data, this risk is moreover not financially insurable and thus, farmers have to manage this risk through means other than financial insurance. On-farm risk management includes – but is not limited to – spatial diversification of farmland, choice of stocking rate and production system and herd organization (cf. Obrich 2012: 30ff). For example, it is standard farming practice to divide the area of farmland into small paddocks that are grazed for short periods (10 to 14 days) and subsequently rested for a minimum of two months (rotational grazing). One focus of this paper will thus be to investigate the interrelation of stocking rates and environmental risk since the choice of stocking rate has been established as the farmer's central element of risk management in the literature (McArthur and Dillon 1971, Karp and Pope 1984, Rodriguez and Taylor 1988, Torell, Lyon and Godfrey 1991 and Quaas et al. 2007).

3 Methods

We review the methods used in this paper. We start by introducing the data set and its peculiarities in Section 3.1. In Section 3.2, we briefly review the Pareto distribution and the intricacies involved when fitting it to empirical data.

3.1 Data

We use a unique and highly detailed data set of 399 Namibian commercial cattle farmers that have been surveyed in 2008 and 2009 by a mail-in questionnaire and field experiments. Approximately 19% of the 840,000 (cf. Olbrich, Quaas and Baumgärtner 2012) heads of cattle commercially farmed in Namibia belonged to farmers that participated in our survey. In terms of rangeland area, our survey covers 21.5% of all rangeland that is officially designated as commercial cattle farming region.[2] The details of the complete survey and its methodology, including the data acquisition process and limitations, can be found in Olbrich, Quaas and Baumgärtner (2012). A complete copy of the survey questionnaire can be found in Olbrich, Quaas and Baumgärtner (2009). In the following, we give a brief overview of those variables of the survey relevant to the present paper.

Farm size is operationalized in two ways, number of cattle held on the farm and area in hectares. Each cattle number record consists of two numbers, one for the number of cattle at the beginning of dry season (April/May) and one for cattle number at the beginning of wet season (November). We refer to the average value of these two numbers when we speak of 'herd size' or 'cattle number' which serves the purpose of correcting for possible seasonal effects. In addition, we constructed the stocking rates from the so-obtained herd sizes and rangeland areas as stated in the questionnaire answers by the farmers.

In Namibia's semi-arid regions, meteorological stations are rare at best and records often have considerable gaps (Olbrich 2012). Therefore, the data set uses simulated precipitation data from the calibrated REMO model[3] (Jacob 1997, Jacob and Podzun 2001). These simulated data contain rainy-season (November–April) precipitation in millimeters and its standard deviation at the farm location as 30-year average from 1978–2008. We take the coefficient of (inter-annual) variation following from these data as a measure for the environmental risk unique to each farm. We illustrate the spatial distribution of the coefficient of inter-annual variation in precipitation in Figure 2.

Risk preferences were elicited using the well-established adapted price list format (cf. Binswanger 1980, Holt and Laury 2002, Andersen et al. 2006). Concretely, Olbrich, Quaas and Baumgärtner (2009) offered each farmer the hypothetical choice between participating in a cattle auction with uncertain payoffs and selling a certain number (50 weaners) of their cattle to a trader who offered secure payments in each round. The auction scenario was to sell all of the 50 weaners for either N\$ 90'000 (1'800 N\$ per head) or N\$ 130'000 (2'600 N\$ per head) with equal probabilities $p_1 = p_2 = 0.5$ each, so that expected payoff was N\$ 110'000 (2'200 N\$ per head).[4] Conversely, the trader scenario consisted of six

[2]These figures are based on numbers given in Olbrich (2011)

[3]This is a model developed particularly for simulation of regional climates.

[4]On 2008 average, N\$ 1'000 corresponded to US\$ 121.07 (World Bank 2013), and the average per kilogram

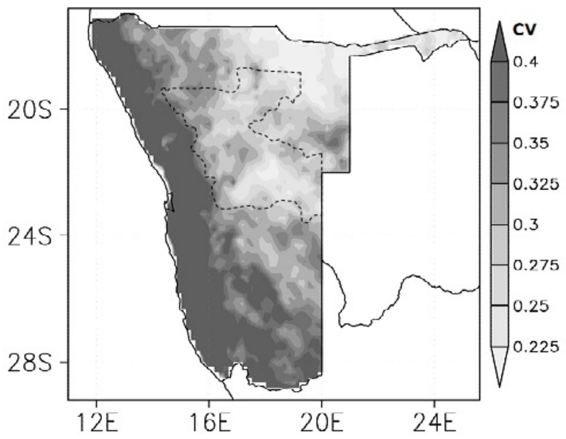


Figure 2: Spatial distribution of the inter-annual coefficient of variation of total rainy season precipitation for the period 1978–2008 and Namibia's main commercial cattle farming area (dashed line), re-printed from Olbrich (2012).

secure offers for the cattle that started at N$ 100'000 and increased in steps of N$ 2'500 to bring the last offer to N$ 112'500. The actual item from the questionnaire that the farmers had to consider can be seen in Figure 3. Essentially, the setup means that the 'switchpoint' at which each farmer switched from selling at the auction to selling to the trader characterizes her risk attitude: the later she switches from the uncertain auction to the trader, the larger her certainty equivalent given the lottery, and the more risk loving she is. In this paper, we use the following conversion from switchpoint to risk attitude: 1 through 4 – risk-averse, 5 – risk-neutral, 6 and 7 – risk-loving, where a switchpoint of 7 means that the trader was never chosen and hence the auction always preferred. In other words, a switchpoint from one to four means a positive risk premium, at five, the risk premium is zero, and six or seven (no switchpoint) means a negative risk premium.

Not every data record is complete in every variable. Depending on the research question, we have the following population sizes: In Section 4.2, we have $N = 391$ for the fit of the Pareto distribution to the area data, $N = 351$ for the fit of the cattle data and $N = 347$ for the fit of the stocking rates. In Section 4.3, we base our calculations on 258 records containing complete data for cattle count as well as environmental risk and on $N = 156$ whereever switchpoints are involved.

price for weaners was 11.88 N$ (The Namibian 2010). Hence, a 180 kg weaner could roughly fetch 2'140 N$.

Scenario	Auction	Trader
1: The trader offers you **N$ 100 000**. What would you prefer?	Sell at auction ☐	or sell to trader ☐
2: The trader offers you **N$ 102 500**. What would you prefer?	Sell at auction ☐	or sell to trader ☐
3: The trader offers you **N$ 105 000**. What would you prefer?	Sell at auction ☐	or sell to trader ☐
4: The trader offers you **N$ 107 500**. What would you prefer?	Sell at auction ☐	or sell to trader ☐
5: The trader offers you **N$ 110 000**. What would you prefer?	Sell at auction ☐	or sell to trader ☐
6: The trader offers you **N$ 112 500**. What would you prefer?	Sell at auction ☐	or sell to trader ☐

Figure 3: The six scenarios of the lottery choice experiment. Re-printed from Olbrich, Quaas and Baumgärtner (2012)

Despite the very good quality and unique contents, a few facts limit the extent of the analysis presented here. Because participation in the survey was on a voluntary basis, our sample is self-selected. However, we have no reason to believe that criteria for self-selection should be related to the variables used in this analysis. Another limitation is caused by the nature of our precipitation data. Precipitation data is based on 30-year period of precipitation in the rainy season from 1978–2008 while cattle number, rangeland areas and therefore stocking rates are a snap-shot of basically two points in time (November 2007 and April 2008). This naturally limits the potential in the data to investigate whether farmers use the 'opportunistic grazing' strategy as recommended by Beukes, Cowling and Higgins (2002), because one would need data on actual precipitation in the rainy season 2007/08. Lastly, we add that cattle and rangeland figures in the data set are aggregates, possibly over multiple different locations (cf. Olbrich, Quaas and Baumgärtner 2009: 29).

3.2 The Pareto distribution

The Pareto distribution is one of the most well-known theoretical approaches to model empirical size distributions in economics, and also one of the oldest. Italian economist, engineer and sociologist Vilfredo Pareto introduced it in several works as a possible theoretical description of the wealth distribution in Italy (Pareto 1895, Pareto 1896, Pareto 1897a and Pareto 1897b). Although many alternatives have been proposed over the years (e.g. Kleiber and Kotz 2003 for an overview on this), it is still frequently used today (Reed 2001, Reed 2003, Lévy 2009, Ioannides and Skouras 2013). Its probability density function reads

$$p(x) = \frac{1}{\alpha - 1} \left(\frac{x}{x_{\min}} \right)^{-\alpha} \tag{1}$$

with $x > 0$. $\alpha > 0$, which is usually also referred to as Pareto coefficient, describes the tail of the distribution such that the smaller its value, the heavier (i.e. longer) the tail. $x_{\min} > 0$ is the cutoff value above which the distribution actually follows a power law, i.e. a Pareto distribution such that a double-logarithmic plot of power-law data follows a straight line.

The straight line appearance of power laws in double-logarithmic plots has quite often been used as a graphical diagnostic criterion. However, telling whether empirical data follow a certain distribution in a more satisfactory way is a pretty tricky question (cf. Clauset, Shalizi and Newman 2009, Engler and Baumgärtner 2015). Here, we use the method proposed by Clauset, Shalizi and Newman (2009) to fit the Pareto distribution to our data and to see whether it provides a plausible description of the it. This method has three advantages: (1) It employs the method of maximum likelihood, which performs better than the method of least squares (White, Enquist and Green 2008, Clauset, Shalizi and Newman 2009), (2) It is a valid test for the power-law hypothesis where other tests such as Kolmogorov-Smirnov or Cramér-von-Mises have been known to run into problems (cf. Bubeliny 2011, Engler and Baumgärtner 2015), and (3) at the same time, it provides an objective method to determine the cutoff value $x_{\min}$. We illustrate the results of the method in the next section in Figure 5, and give the numerical details in Table 3.

4 Results

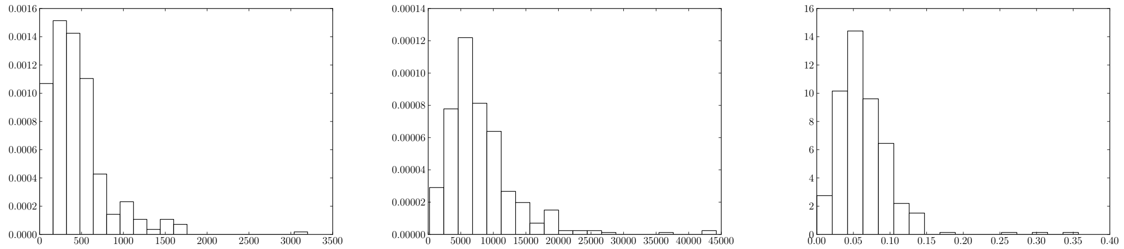
This section lists and discusses our results. In Section 4.1, we provide descriptive statistics for the data set, along with some illustrative comparisons. Section 4.2 gives a short introduction to the Pareto distribution and how we can use it as a starting ground for further analysis and group comparisons, before actually displaying our fitting results. Section 4.3 then reports the results of the group comparisons.

4.1 Descriptive statistics

Tables 1 and 2 list some descriptive statistics of the data with Table 1 focusing on farm size, cattle numbers and the stocking rate, which is the ratio of these two, and Table 2 on precipitation and risk attitude data. The average farm from our sample had 450 cattle on farm with a standard deviation (SD) of 369, and a size of 7970 ha (SD = 5504 ha). For comparison, in 2010, the average U.S. cattle farm contained 44 cows on a land area of 169 hectares (U.S. Department of Agriculture 2010). The U.S. state with the largest average acreage per farm, Wyoming, reported an average of 1112 hectares per farm (U.S. Census 2012). The largest farm from our sample has with 42244 hectares (approx. 422 km^2) roughly the same size as Barbados while the median farm is with 68 km^2 still roughly as big as San Marino (61 km^2). The smallest farm in our sample is still as big as Monaco (2 km^2). The values for skewness and kurtosis indicate that the distributions are all comparably right-skewed and leptokurtic. The Gini coefficients in the present sample for the variables cattle number (G = 0.39) and area (G = 0.34) are roughly half the size of the numbers reported by Eastwood, Lipton and Newell (2010) for the distribution of farm sizes in the United States in the 1990s (G = 0.78) and slightly smaller than what they report for Sub-Saharan Africa (G = 0.50). Figure 4 presents histograms of overall distributions for all three variables.

Table 1: Descriptive statistics of the overall sample of Namibian commercial cattle farms for the two size characteristics cattle number and area, and for the stocking rate. LSU = livestock units.

descriptive statistic	cattle [number]	area [ha]	stocking rate [LSU/ha]
sample size	351	391	347
minimum value	1	200	0.00013
maximum value	3200	42244	0.357
mean	450	7970	0.063
median	369	6800	0.058
standard deviation	361	5504	0.037
skewness	2.37	2.50	2.84
kurtosis	10.48	11.00	17.08
Gini coefficient	0.394	0.336	0.282



(a) cattle number (heads) (b) area (ha) (c) stocking rate (heads/ha)

Figure 4: Distribution of commercial cattle farm sizes in Namibia as measured in cattle number (a), rangeland area (b) and stocking rates (c).

Table 2: Descriptive statistics of the data set concerning precipitation and risk attitudes. Statistics are reported along with 95% confidence intervals in brackets where applicable.

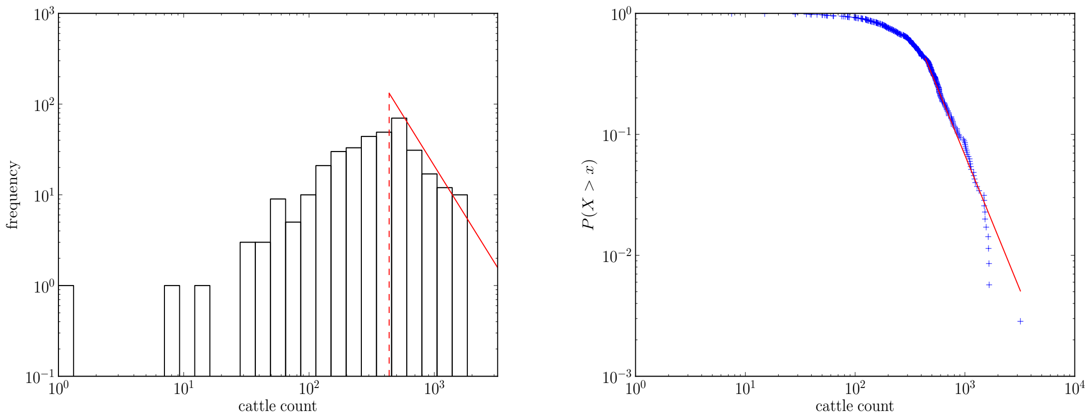
descriptive statistic	value
average precipitation [mm]	270.70 (10.76)
Gini (precipitation)	0.179
median precipitation [mm]	281.54
minimum/maximum precipitation [mm]	63.35 / 460.02
average variation coefficient	0.285 (0.005)
Gini (variation coefficient)	0.073
median variation coefficient	0.280
minimum/maximum variation coefficient	0.213 / 0.475
average switchpoint	4.79 (0.14)
Gini (switchpoints)	0.117
median switchpoint	5

The average annual precipitation in the Namibian sample is 271 mm (Table 2) which compares to cities such as Phoenix, AZ (211 mm) or San Diego, CA (274 mm). As a general rule of thumb in meteorology, everything below 200 mm (7.9 in) of annual precipitation is considered very dry. The driest farm in the sample received only 63 mm of rain per year which roughly corresponds to the driest city in the U.S., Yuma, AZ. On the other hand, the wettest farm in the sample received on average 460 mm of precipitation per year. The very high variability in inter-annual precipitation is reflected by an average coefficient of variation of 0.285 over all farms. In contrast, it seems from Figure 1 that most places in North America and Europe seem to have a climate characterized by C_v values from 0.10 to 0.15.

4.2 Pareto distribution

Table 3: Fitting results of the Pareto distribution to our data (from left to right): data set, sample size N, the cutoff value of the Pareto distribution $\hat{x}_{\text{min}}$, estimated 'tail index' $\hat{\alpha}$ along with 95% confidence interval, number of farms in Pareto branch of distribution $n \geq x_{\text{min}}$ and p-values. p-values significant at the 10% level are marked with an asterisk.

data set	N	$\hat{x}_{\text{min}}$	$\hat{\alpha}$	$n \geq x_{\text{min}}$	p-value
avg. cattle count	351	436	3.22 (0.02)	149	0.33*
rangeland area	391	7000	3.25 (0.02)	190	0.01
stocking rate	347	0.051	3.42 (0.02)	215	0.01



(a) histogram

(b) survival function

Figure 5: Best fit of the Pareto distribution to the average herd size data: panel (a) shows a log-log histogram along with the best fitting Pareto distribution including an extra marking of the cutoff value x_{min} while panel (b) shows the so-called survival function and the best Pareto fit.

In Table 3, we list the results of the fitting procedure and the hypothesis test. We have used the originally proposed significance level, which is 10%, and estimates are based on 2500 Monte Carlo replications, so that p-values are ± 0.01 accurate (cf. Clauset, Shalizi and Newman 2009). The test rejects the power-law hypothesis for the farm area and stocking rate data ($p = 0.01$ each), but does not reject it for the average cattle data ($p = 0.33$). In what follows, we will focus on the average cattle number data set. Overall, the test suggests that the Pareto distribution is a statistically plausible description for 42.5% of the data (149 out of 351 farms) with an estimated minimum farm size of $\hat{x}_{\min} = 436$. Figure 5 illustrates these findings with a double-logarithmic histogram and the corresponding survival function, along with the best Pareto fit in each figure.

While the Pareto distribution is not the only plausible probability distribution for this data set (cf. Engler and Baumgärtner 2015 for a detailed take on this issue), it does separate the farms into two groups with respect to the cutoff value $x_{\min}$. Since this distinction seems fairly neutral and objective, we consider this as one possible starting point that calls for further investigation concerned with the relation of environmental risk and the farmers' risk attitudes in Section 4.3.2. Moreover, we will refer to farms in the Pareto branch of the distribution ($x \geq x_{\min}$) as 'Paretian' and accordingly, we will call the other farms 'non-Paretian' ($x \leq x_{\min}$).

Based on our findings so far, we organize our investigations into three sections that reflect the farmer's affiliation to the following groups: (1) overall sample, (2) affiliation to the two branches of the distribution (Paretian, non-Paretian) and (3) affiliation to the risk preference group. We report the findings in the following section.

4.3 Farm size, environmental risks and risk preferences

We take up the results obtained so far in the following manner: Section 4.3.1 investigates the correlations between precipitation data and farm sizes for the overall sample, before we look at the same question for the two branches of the distribution resulting from the fit of the Pareto distribution in Section 4.3.2. Finally, we compare the subgroups of farmers that result from their risk preferences and scrutinize how the different risk attitudes affect the farm size distribution in Section 4.3.3.

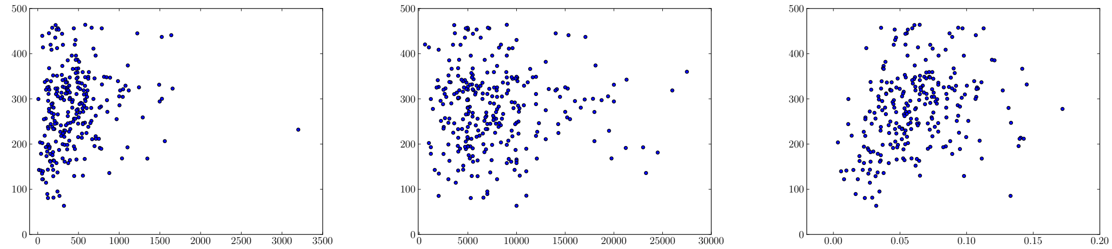
4.3.1 Overall sample

In Table 4, we present the Spearman correlations between herd size and precipitation data (upper section of table), mean farm size with precipitation data (middle section of the table) and stocking rates with precipitation data (lower section of table). The effect sizes classify the strength of effect for each pair of correlatives after Cohen's scale (cf. Cohen 1988: 82). Figure 6 shows the associated scatter plots.

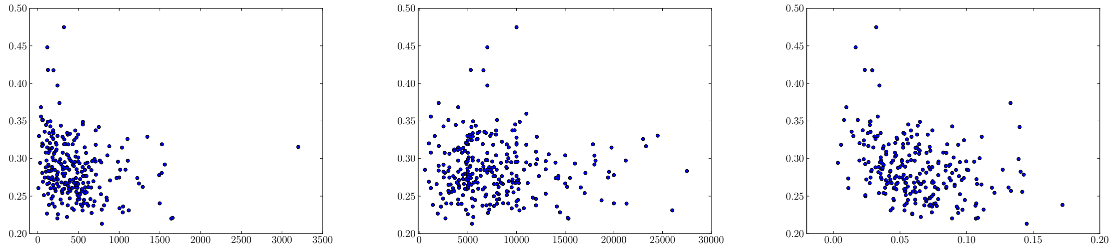
Table 4: Spearman correlation coefficients of the different size measures with precipitation variables. p-values are reported for the null hypothesis 'true ρ is equal to zero', and effect sizes are classified according to Cohen's scale : $0.1 \leq \rho < 0.30$: small, $0.30 \leq \rho < 0.50$: medium, $\rho \geq 0.50$: large.

herd size correlated with	Spearman's ρ	p-value	effect size
mean precipitation	0.24	< 0.001	small
coefficient of variation	-0.29	$< 10^{-5}$	small
area correlated with			
mean precipitation	-0.01	0.81	none
coefficient of variation	-0.01	0.89	none
stocking rate correlated with			
mean precipitation	0.34	$< 10^{-7}$	medium
coefficient of variation	-0.34	$< 10^{-7}$	medium

While we do not find any significant correlation between area and any of the precipitation variables ($\rho = -0.01$, $p = 0.81$ and $p = 0.89$), we do find significant correlations between herd size and mean annual precipitation ($\rho = 0.24$, $p < 0.001$) and herd size and variation coefficient ($\rho = -0.29$, $p < 10^{-5}$), albeit with small effect sizes. We find the strongest correlation coefficients when looking at the stocking rate: there is again a positive correlation with mean annual precipitation ($\rho = 0.34$) and a negative one with variation coefficients ($\rho = -0.34$). Both correlations have a medium effect size and are statistically highly significant as $p < 10^{-7}$.



(a) $\rho = 0.24$ (b) $\rho = -0.01$ (c) $\rho = 0.34$



(d) $\rho = -0.29$ (e) $\rho = -0.01$ (f) $\rho = -0.34$

Figure 6: Scatter plots for all pairs of variables listed in Table 4, based on the complete data set. The upper row of graphs (Figs. a through c) shows scatter plots of annual precipitation and all size variables herd size, area and stocking rate. The lower row of graphs (Figs. d through f) shows scatter plots of coefficient of variation of inter-annual precipitation and all size variables.

4.3.2 Distribution branches

Table 5 lists the correlation coefficients for the same pairs of correlatives as in the previous section, but this time ordered according to the fitting results of the Pareto distribution to the data. This is to say that we compare farms larger than the cutoff value x_{min} with the ones smaller than this cutoff value. We base this distinction on the sole statistically plausible fit of the Pareto distribution to our data, which was to the average herd size data. Thus, we use $x_{\text{min}} = 436$ in what follows.

In terms of direction of correlations, their strengths and significance, we roughly recover the results from the overall sample. Because of reduced sample sizes ($N = 110$ and $N = 148$ as compared to $N = 258$ in the previous section), effect sizes are slightly smaller. Overall, there are no significant correlations in the 'Paretian' subgroup (i.e. for farms with herd size $x \geq 436$). However, we do find significant correlations for all pairs of correlatives in the 'non-Paretian' subgroup (i.e. for farms with herd size $x < 436$), the strongest one being again the one between stocking rate and variation coefficient ($\rho = -0.42$, $p < 10^{-6}$). All correlations in this branch are very unlikely to result from pure chance as p-values are consistently less than or equal to 0.01. These results suggest that there is indeed a difference between Paretian and non-Paretian farms, but the question remains what kind of difference that might be. We look at this in more detail in Table 6.

Table 5: Spearman correlation coefficients of size with precipitation variables: Comparison of the two branches suggested by the fit of the Pareto distribution. The alternative hypothesis H_1 was 'true ρ is not equal to zero'.

Paretian farmers ($N = 110$)			
correlatives	Spearman's ρ	p-value	effect size
mean herd size – precipitation	0.00	0.99	none
mean herd size – coefficient of variation	−0.01	0.91	none
stocking rate – precipitation	0.13	0.17	none
stocking rate – coefficient of variation	−0.06	0.53	none
non-Paretian farmers ($N = 148$)			
mean herd size – mean precipitation	0.24	< 0.01	small
mean herd size – coefficient of variation	−0.23	< 0.01	small
stocking rate – mean precipitation	0.43	$< 10^{-7}$	medium
stocking rate – coefficient of variation	−0.42	$< 10^{-6}$	medium

Table 6 lists our results concerning mean values of switchpoints (i.e. risk attitudes), farm sizes and coefficient of variation of inter-annual precipitation. Since we do not make any assumption about the distribution of these variables, we used the Mann-Whitney U-Test to test for significant differences in these mean values. Because average herd size and rangeland area differ significantly in the two branches by construction, we do not report p-values for differences in these variables. We find that farmers in the two branches have roughly the same risk preferences (mean of non-Paretian farmers: 4.65 as compared to 4.83 for Paretian farmers) as 95% confidence intervals overlap quite a bit. Consequently, we cannot reject the possibility that the data would realize as observed by mere chance ($p = 0.20$). However, we find that Paretian farmers face quite different environmental risks (in terms of C_v-values) than non-Paretian farmers and this difference is very unlikely to result from pure chance as neither the 95% nor the 99% confidence intervals of the average coefficients of variation overlap (0.274(0.006) for Paretians compared to 0.294(0.007) for non-Paretians), in addition to a p-value smaller than 10^{-4} and a medium effect size of 0.55. Moreover, average stocking rates are lower for Paretian farms than for non-Paretian ones (0.051 compared to 0.077), an effect which not only is highly significant ($p < 10^{-13}$) but also features a large effect size (Cohen's $d = 0.96$), while Paretian farmers have significantly ($p = 0.003$) more mean annual precipitation (296.2 mm compared to 263.9 mm), which is a moderately strong effect (Cohen's $d = 0.37$).

Table 6: Paretian and non-Paretian branches of the empirical distribution in comparison. p-values have been calculated with the Mann-Whitney U Test with H_0 being 'true shift in location is equal to 0'. Where meaningful, we provide 95% confidence intervals in brackets and effect sizes (Cohen's d) to supplement the results of the statistical hypothesis tests. Classification of effect sizes follows Cohen's original suggestion ($0.2 \leq d < 0.5$: small; $0.5 \leq d < 0.8$: medium; $d \geq 0.8$: large).

variable	Paretian	non-Paretian	p	Cohen's d (effect size)
average switchpoint	4.65 (0.26)	4.83 (0.26)	0.20	0.15 (none)
average herd size	752 (73)	236 (18)	N/A	N/A
average rangeland [ha]	10845 (1091)	5517 (430)	N/A	N/A
average stocking rate [LSU/ha]	0.051 (0.004)	0.077 (0.005)	$< 10^{-13}$	0.96 (large)
average precipitation [mm]	296.2 (14.0)	263.9 (15.4)	0.003	0.37 (small)
average variation coefficient	0.274 (0.006)	0.294 (0.007)	$< 10^{-4}$	0.55 (medium)

4.3.3 Risk preference groups

In Table 7, we list the variables describing the risk-preference subgroups together with 95% confidence intervals and effect sizes (upper part), together with Spearman correlations of size and precipitation variables (lower part). Overall, we find that the risk-preference groups are fairly similar in terms of the key characteristics such as herd size, rangeland area, stocking rates and coefficient variation of variation of inter-annual precipitation. In fact, 95% confidence levels always overlap (Table 7). Regarding correlations of size and precipitation variables (lower part of Table 7), we find slightly negative correlations of herd sizes and variation coefficients, but effect sizes are small or medium by only a very slim margin ($\rho = -0.34$ for risk-neutral and $\rho = -0.23$ risk-loving subgroup). We do not find any correlation at all for the risk-averse subgroup, for neither herd size related correlative. These values are very similar to the effects observed in the overall sample (cf. Table 4). The correlations of stocking rates and variation coefficients have the same direction, but are slightly stronger which gives small effect sizes for the risk-averse ($\rho = -0.29$) and the risk-loving subgroups ($\rho = -0.44$). As to correlations of herd size or stocking rate with mean annual precipitation, the only subgroup with statistically significant correlations is the risk-loving one, except for herd size and mean precipitation, where we also find a statistically significant value ($\rho = 0.30$) with medium effect size. The risk-loving subgroup features a moderately positive correlation of herd size and precipitation ($\rho = 0.34$) and a large positive correlation between stocking rates and precipitation ($\rho = 0.58$).

Table 7: Key characteristics of risk preference groups. Effect size classification and 95% confidence intervals are given in brackets. Spearman correlation coefficients are additionally marked with an asterisk when statistically significant at the 5% level.

	risk preference group		
variable	risk-averse	risk-neutral	risk-loving
sample size	52	64	40
average switchpoint	3.50 (0.26)	5.00 (0.00)	6.08 (0.08)
average herd size	507 (99)	434 (74)	461 (122)
median herd size	451	392	368
average rangeland [ha]	8705 (1448)	7804 (1070)	7412 (1253)
median rangeland [ha]	8000	6824	6535
average stocking rate [LSU/ha]	0.066 (0.009)	0.058 (0.006)	0.063 (0.010)
average precipitation [mm]	267.8 (26.2)	284.3 (19.3)	269.5 (27.6)
average variation coefficient	0.286 (0.012)	0.280 (0.008)	0.286 (0.013)
Spearman's ρ (herd size – precipitation)	0.00 (none)	0.30* (medium)	0.34* (medium)
Spearman's ρ (herd size – variation coeff.)	0.00 (none)	-0.34* (medium)	-0.23* (small)
Spearman's ρ (stocking rate – precipitation)	0.22 (small)	0.24 (small)	0.58* (large)
Spearman's ρ (stocking rate – variation coeff.)	-0.29* (small)	-0.18 (small)	-0.44* (medium)

Table 8 compiles the results of the Mann-Whitney U test for mean value comparisons for the relevant variables from Table 7. We do not find a single pair of subgroups where differences in mean values of any of these variables are somewhat close to the 5% level.

Table 8: p-values for mean-value comparisons of the risk preference groups, which have been calculated with the Mann-Whitney U Test with H_0 being 'true shift in location is equal to 0'. We do not find any significant differences in mean values.

groups compared	... with respect to mean values in ...				
	herd size	area	stocking rate	precipitation	variation coeff.
risk-averse – risk-neutral	0.373	0.488	0.311	0.257	0.629
risk-loving – risk-averse	0.312	0.277	0.697	0.747	0.829
risk-neutral – risk-loving	0.794	0.543	0.591	0.432	0.572

As to the question regarding the interrelation of risk preferences and inequality in the subsamples, we list the values of the six most common inequality indices (see, for example, Cowell 2011) in Table 9. As we go through the risk attitude groups from risk-averse to risk-loving, we can see that there is a clear trend towards increasing inequality in cattle herd sizes that is independent of the choice of the inequality index. The average percentage increase in inequality indices is 23.1%.

Table 9: The six most common inequality measures with respect to herd size distribution for the three risk preference groups. The unweighted average increase in inequality going from the risk-averse to the risk-loving subgroup is 23.1%.

	risk preference group			
inequality index	risk-averse	risk-neutral	risk-loving	abs. % change
Gini	0.363	0.362	0.411	13.2
Ricci-Schulz	0.257	0.259	0.295	14.8
Atkinson	0.107	0.118	0.139	29.9
Theil	0.216	0.219	0.284	31.5
generalized entropy	0.219	0.238	0.289	32.0
coefficient of variation	0.696	0.672	0.815	17.1

5 Discussion

We discuss our results in the same order as just reported: Section 5.1 looks at the results for the overall sample, Section 5.2 discusses the results for the distribution branches, and Section 5.3 looks at the group comparisons based on risk preferences.

5.1 Overall sample

The correlations that we find for the precipitation and herd size pairs of variables are in agreement with intuition: The more precipitation a farm gets on average per year, the more cattle the farm can support because there is higher grass production resulting from this higher precipitation. The positive and highly significant correlation with small effect size provide solid evidence for this feedback possibly underlying our data. On the other hand, the more uncertain the precipitation, the more uncertain it is how much cattle the land can support. One possible strategy to deal with this situation would be to choose a lower amount of cattle to be reared on the farm. From our data, it seems that this is what farmers predominantly do when faced with high precipitation risks. The same effect can be seen in the correlations of stocking rates and precipitation variables, which substantiates the crucial role of the stocking rate in farm and rangeland management as already suggested in various other works (McArthur and Dillon 1971, Karp and Pope 1984, Rodriguez and Taylor 1988, Westoby, Walker and Noy-Meir 1989, Torell, Lyon and Godfrey 1991).

There are no correlations whatsoever for the area-precipitation pairs of variables. This is surprising because it would have been possible that farmers confronted with high inter-annual variation of precipitation and low mean annual precipitation try to gain access to larger areas of land that are also spatially diversified (cf. Quaas et al. 2007). This would be possible because there is a quite well-developed and functioning land market in Namibia (Olbrich 2012). Thus, we would have expected a positive correlation between area and coefficient of variation of inter-annual precipitation. However, there is no evidence for such an effect showing in our data. We find this striking because a strategy that seeks to hedge and diversify downside risks resulting from excessive variability in precipitation would be optimal at least for risk-averse farmers, given reasonable transaction costs.

5.2 Distribution branches

In Table 6, we have seen that Paretian farmers face on average significantly less inter-annual variability in rainfall, i.e. environmental risk. One possible explanation for our these findings could be that more stable environmental conditions reduce the Paretian farmers' income risks so that less resources and financial capital had to be spent on financial insurance, self-insurance and possibly self-protection. This capital could then be invested in additional cattle to be reared on farm. As a result of these effects – more certainty regarding forage production and general rangeland quality leading to less financial strain on the farmer – farms had, ceteris paribus, more opportunities to augment cattle production. On the other hand, confronted with greater environmental uncertainty, non-Paretian farmers might have a greater need for diversification of this larger risk. They might either tend to opt for various small farms at different locations or choose to become part-time farmers more often than their Paretian colleagues. Both of these mechanisms would foster smaller herd sizes and less rangeland area in the non-Paretian branch.

The data give us no reason to assume that risk preferences might be distributed inhomogeneously over the two groups. This seems surprising because two ways of arguing seem a priori plausible: On one hand, one could have reasoned that non-Paretian farmers were less willing to take risks than their Paretian colleagues and so would tend to refrain from expanding their businesses, because expansion usually comes with higher financial risks. On the other hand, it would have also been imaginable that a 'no risk no gain' mentality could have led to the numbers that we found because it is possible that some of the farmers owning farms smaller than $x_{\min}$ today could have been forced to sell substantial parts of their herd in the aftermath of a risky strategy gone wrong at some earlier point in time. Both of these explanatory models would suggest at least some inhomogeneity regarding risk preferences in the two subgroups. However, it seems that our data does not support this view.

The strongest effect based on our mean value comparison between the two subgroups from the Pareto distribution is the difference in stocking rate mean value. Smaller farms (in terms of average herd size) have on average considerably (51%) more cattle per hectare than the larger ones. The average stocking rate of the non-Paretian farms is 0.077 LSU/ha which is only slightly below what Olbrich, Quaas and Baumgärtner (2013) report as average grazing capacity (0.080 LSU/ha[5]) for the sample. We interpret this as a possible fixed-costs effect: small farms in terms of herd size usually also have less rangeland. In order to be profitable in any given year, farms need to have a certain minimum herd size and this minimum herd size might be larger than actually suggested by grazing capacity. In the short term, this could be a viable strategy which might explain the much higher average stocking rates with smaller farms. It has also been suggested that risk-neutrality might imply optimality of higher stocking rates (Rodriguez and Taylor 1988). While there is no significant difference in average switchpoints here, we will consider this theory again in the next section.

5.3 Risk preference groups

We did not find any detectable difference in any of the average size and precipitation variables between the three risk preference groups. Our finding contradicts the hypothesis from Olbrich (2012) according to which more risk-averse farmers tend to self-select by operating farms with on average lower environmental risk. This apparently missing self-selection might be explained by several factors. First, a farm is not always build from scratch with full freedom of choice of all relevant parameters (location, rangeland area and the like). In practice, chance and randomness may play a key role, but also lack of information. Moreover, if a farmer buys or leases an already existing farm from someone else, the location is externally given and there is nothing the farmer can do except for accepting or not accepting the offer of buying or leasing that particular farm at the price named. Furthermore, factors such as proximity to hometown or close relatives might play a large role in these decisions, but these are not captured in the data. It is also not uncommon that farms are passed on within the family. Lastly, we have used the full sample regarding switchpoints here ($N = 156$), while Olbrich (2012) had to exclude certain farmers for econometric reasons bringing their sample size down to $N = 99$.[6]

There is no difference in mean stocking rates between the three risk preference groups

[5]This value is based on the information provided by the farmers in the questionnaire.

[6]Olbrich's study focused on the determinants of risk preferences of the farmers in the sample. One key hypothesis was that risk preferences are critically influenced by life-history factors such as environmental risk experienced prior to age 18 and number of years living on the current farm. Thus, they had to remove all those farmers for which these data were not complete.

(Table 8). In the light of existing theories of rangeland management under uncertainty, this finding seems especially striking. For example, in their 2007 model, Quaas et al. show that a myopic and sufficiently risk-averse farmer will have a very conservative strategy – i.e. low stocking rates – as optimum. For our data, this would imply that our risk-averse subgroup should have at least the smallest stocking rate among all subgroups if they actually were risk-averse non-satiated expected utility maximizers. For risk-neutral farmers, Rodriguez and Taylor (1988) suggest that high stocking rates may have larger expected net present values than low stocking rates. However, we cannot find evidence for the presence of such effects in our data. Altogether, it seems that risk preferences do not make a statistically detectable difference in any of the size and precipitation variables.

It is quite striking that we find the strongest effects in terms of correlations of size and precipitation variables in all but one case in the risk-loving subgroup (cf. Table 7). It seems that a good part of the correlations observed for the overall sample (cf. Section 4.3.1) comes from the risk-loving farmers. Particularly the stocking rates are strongly correlated with precipitation ($\rho = 0.58$) and inter-annual coefficient of variation of precipitation ($\rho = -0.44$). We find the latter observation puzzling, because we would have expected to see the strongest negative correlation between size variables and coefficient of variation in the risk-averse subgroup, not in the risk-loving one. On the other hand, the risk lovers should in theory have featured a positive correlation, not a negative one. Again, there is no evidence for self-selection of farmers into locations that suit their risk preference.

The results shown in Table 9 clearly suggest that a more risk-loving attitude among farmers comes with a more unequal distribution of herd sizes. This is in agreement with intuition: under the standard assumptions, utility functions of risk-loving farmers are convex, i.e. $U'(y) > 0$ and $U''(y) > 0$ for every positive income level y. This implies that the utility drawn from a potentially high payoff y_H outweighs the utility from a potentially very low payoff y_L in expected utility considerations, even if there is only a slim chance of actually receiving y_H. Hence, in a sample of risk-loving farmers, we would, ceteris paribus, expect to see a 'more unequal' distribution than in a sample of risk-neutral or risk-averse farmers, because risk-loving farmers will tend to choose riskier strategies which might either leave them very well or very worse off. This is exactly reflected by our sample data: in Table 9, six distinct inequality indices show a consistent trend suggesting that less risk-aversion comes with greater inequality in herd sizes. We acknowledge that the measurement of inequality in any given distribution is in itself a very broad task and that the various measures feature multiple problems (Cowell 2011, Heinemann 2008). Nonetheless, we argue that the observed trend in six independent and technically quite distinct indices should allow for the interpretation that we have given here.

6 Conclusion

In this study, we have investigated the relationship between farm size, environmental risk and risk preferences using a sample of 399 Namibian commercial cattle farmers. With the help of a recent statistical test, we have demonstrated that the Pareto distribution is a statistically plausible description of the tail of the herd size distribution, but not of stocking rate and area distributions. We have used this finding to check for differences between Paretian and non-Paretian farms, and have found the only significant difference to be the average inter-annual variability in rainfall, which is smaller for Paretian farms. Comparing the risk preference groups of farmers, we have not found any supporting evidence for the hypothesis that farmers generally self-select according to their risk preference, i.e. that more risk-averse farmers operate less risky farms. Moreover, we have found that, on average, key size and precipitation characteristics of the farms are evenly distributed over the risk preference groups, but there is evidence that a more risk-loving attitude comes with greater inequality in distribution of herd sizes. Overall, we found correlations to be consistently strongest if stocking rate is a correlative, which supports its importance as key parameter in farm management, in agreement with the literature. However, we did not find evidence for several other hypotheses from the literature on semi-arid rangeland management.

Altogether, we have provided solid evidence for the crucial role of environmental risk in extensive commercial cattle farming in semi-arid rangelands. It seems to us that the stocking rate is indeed central to the farmer as suggested by many theoretical contributions in agricultural economics, while other theories do not hold up that well, at least not in this particular case.

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