EUROPEAN CENTRAL BANK

EUROSYSTEM

Operational Risk: Evidence, Estimates and Extreme Values from Austria

Stefan Kerbl

OeNB / ECB

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Motivation

- Operational Risk as the “exotic” risk type
- Definition: “the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events.” (Basel Committee 2004)
- **Lack of data** is the reason why despite increased attention since becoming an official regulatory risk category, operational risk is still widely quantified by crude measures that assume a proportional relationship between annual gross income and operational losses
- **Availability bias**: scarceness of data leads to lower awareness of operational risk’s importance for banks’ resilience
- Growing awareness due to the infamous events
  – external events (e.g. devastating tsunamis 2004 and 2011)
  – external fraud (e.g. Madoff investment scandal)
  – internal rough traders (e.g. Société Générale 2008 or UBS in 2011)
  – litigation costs (e.g. BNP Paribas 2014)

Current material risk to banks: litigation costs

- BNP Paribas pleaded guilty to falsifying business records and conspiracy in connection with sanctions violations and agreed to pay $8.9 billion, (July 1st, 2014)
- Deutsche Bank AG said it expects to log EUR 894 million of litigation costs in the third quarter 2014 (Bloomberg Oct. 25th, 2014)
- 12 digit number (hundreds of billions) paid by banks over recent years (LSE Conduct Costs Project 2014)
- High profile cases remain open, like market manipulation (LIBOR fixing, FX), misselling of derivatives to public sector entities and sanctions-breakage
- Recent analyst reports predict expected litigation costs for the biggest European banks over the next few years to exceed EUR 70 bn (Credit Suisse, June 2014)
- The European Central Bank's review of bank balance sheets may not be enough to revive investors' confidence in financial institutions because the test does not address litigation risks, UBS AG Chairman Axel Weber said (Bloomberg, Sep. 18th)

  "The market has really moved beyond seeing the major risk in banks' balance sheet."

Introduction

- We want to fight this imbalance

  – relevance on the one hand and data availability on the other –

  by exploring a rich data source

Austrian Loss Data Collection,

- Part of the regulatory reporting system
- Banks report their operational risk events over a certain threshold once a year
- Database consists of more than 42,000 loss events, for which we know – among other things – the event type, the business line it originated and the loss amount rounded to thousands Euro
- Main research questions:
  - Ideal candidate approaches for fitting severity distributions of operational losses
  - Furthermore, we are interested in statistical characteristics of different event types and business lines
- Paper published in the Journal of Operational Risk, Vol. 9, No. 3, pp. 89-123

First Data Exploration

- **Who reports**: Austrian banks and their subsidiaries (not necessarily located in Austria) which calculate their regulatory capital requirement via the Standardized Approach or the Advanced Measurement Approach
  – In total we have 167 banking entities belonging to 20 consolidating entities
- **When**: The first year of observation is 2007 and the most recent year whose operational losses are reported is currently 2012
- The following table shows a simple cross-tabulation of the frequency of loss events across business lines (BLs) and event types (ETs)

	internal fraud	external fraud	employment practices & workplace safety	clients, products & business practices	damage to physical assets	business disruption & system failures	execution, delivery & process management	other	sum
corporate finance	364	88	20	81	32	22	202	0	809
trading & sales	25	85	30	836	37	201	1,736	0	2,950
retail banking	10	22	1	177	13	93	415	0	731
commercial banking	282	2,104	65	942	471	218	1,843	0	5,925
payment & settlement	1,216	15,598	588	2,853	1,330	687	5,669	0	27,941
agency services	33	108	17	120	7	48	365	0	698
asset management	76	737	5	261	47	20	131	0	1,277
retail brokerage	5	11	3	45	24	6	100	0	194
other	27	137	145	511	687	51	264	4	1,826
sum	2,038	18,890	874	5,826	2,648	1,346	10,725	4	42,351

EVENT TYPES	Mode	Median	Mean	Variance	Excess Kurtosis	Maximum	N
Unit of measurement	thou. €	thou. €	thou. €	thou. €^2	thou. €^4	thou. €	loss cases
internal fraud	2	44	528	4,382,031	91	34,000	2,002
external fraud	2	5	120	1,072,583	1,157	62,134	18,598
employment practices & workplace safety	2	7	39	95,018	455	7,500	855
clients, products & business practices	2	4	251	17,175,456	1,189	194,267	5,537
damage to physical assets	1	2	5	738	389	747	2,631
business disruption & system failures	1	3	17	17,993	521	3,527	1,291
execution, delivery & process management	1	3	60	1,163,399	6,963	100,000	10,611

BUSINESS LINES	Mode	Median	Mean	Variance	Excess Kurtosis	Maximum	N
Unit of measurement	thou. €	thou. €	thou. €	thou. €^2	thou. €^4	thou. €	loss cases
corporate finance	2	23	516	6,733,684	114	34,090	770
trading & sales	2	4	119	3,802,951	2,344	100,000	2,941
retail banking	1	2	54	319,121	302	10,365	719
commercial banking	2	9	464	8,088,320	793	117,557	5,751
payment & settlement	1	4	64	2,632,275	8,829	194,267	27,386
agency services	2	3	29	36,590	147	2,593	682
asset management	2	5	52	324,083	895	18,647	1,276
retail brokerage	1	4	67	188,077	164	5,877	193

Let’s get some more feeling about the distribution

- For illustration purpose: BL “payment & settlement”
- Values in thou. EUR

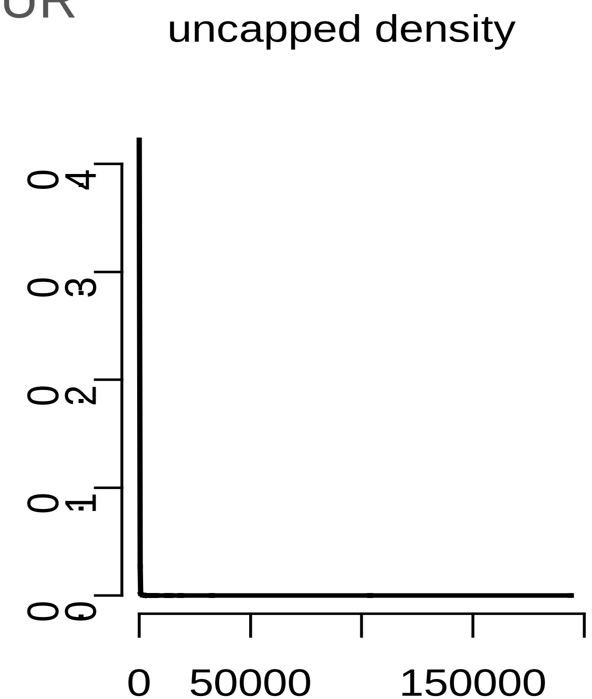
Quantile Level	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	Max	Mean
Loss in thou. EUR	6	7	9	12	18	28	52	119	194,267	64

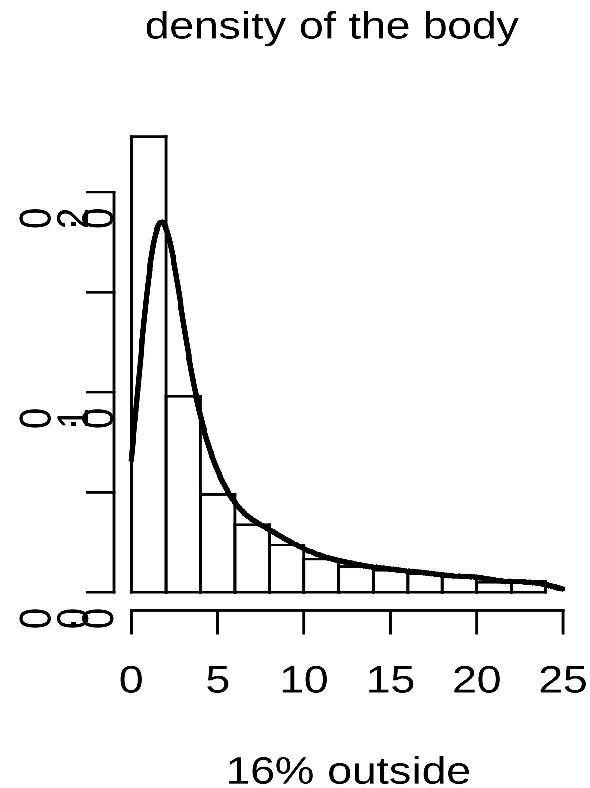
- Max lies far to the right
- Mean lies beyond 90% quantile

⟶ **extreme tails in the data**

Density plots

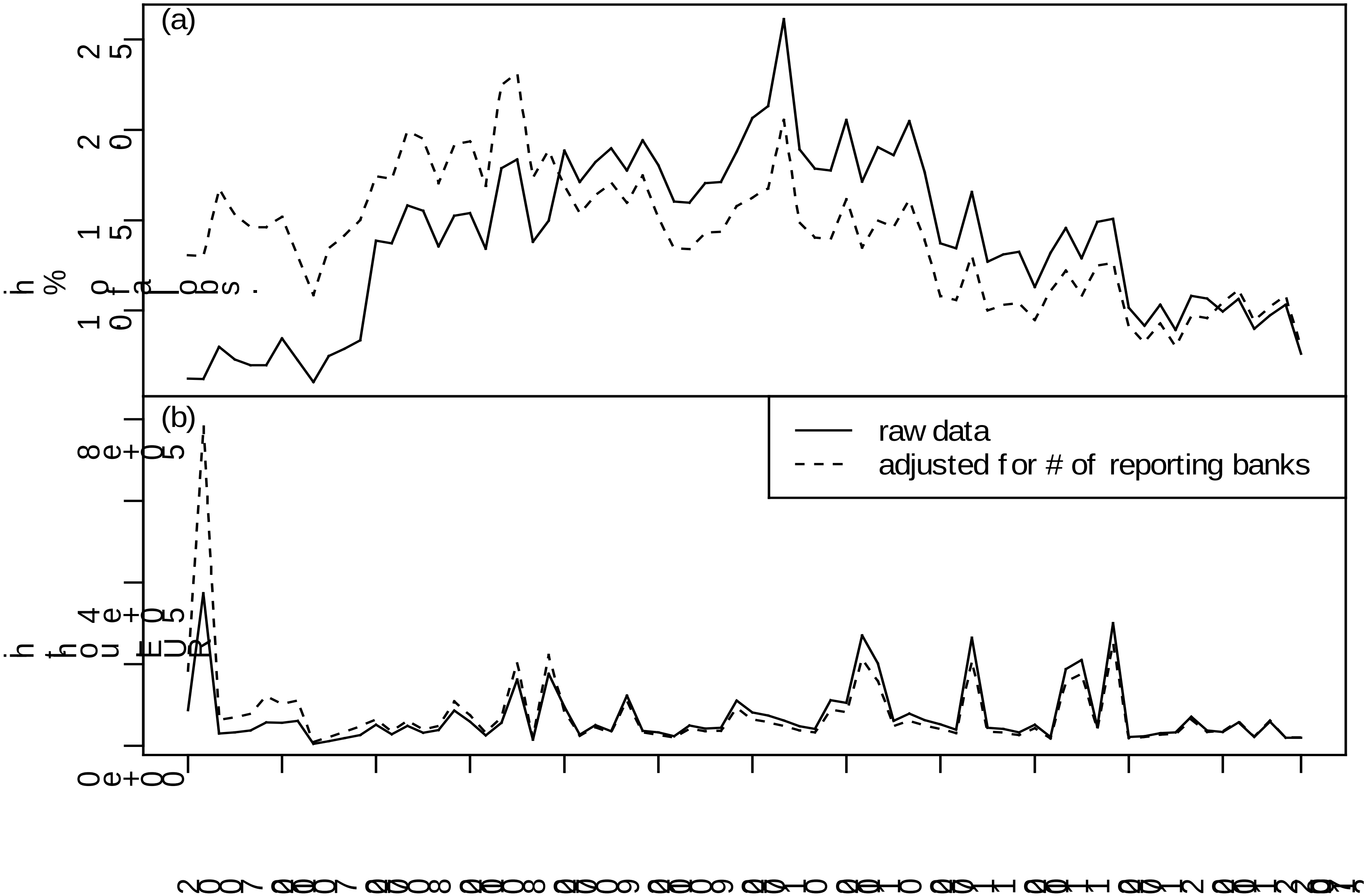
- For illustration purpose: BL “payment & settlement”
- X-axis in thou. EUR





- “L”-shaped density plots if uncapped
- Small cap (e.g. discarding 16% of the data) leads to more common right-skewed density plots

Cross Time Analysis

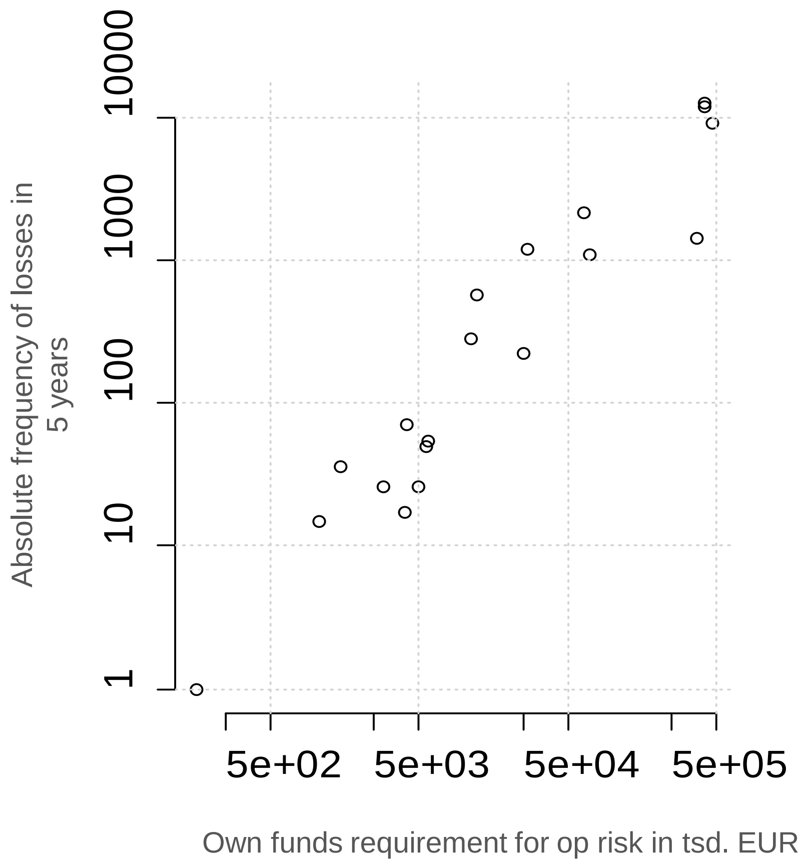


Cross Section Analysis

	Frequency of Losses		Mean Loss		Total Loss Amount	
Correlation used	Pearson	Kendall	Pearson	Kendall	Pearson	Kendall
Interest receivable and similar income	0.86	0.65	-0.04	0.42	0.85	0.70
Net interest income	0.88	0.77	-0.06	0.47	0.85	0.78
Net commission and fee income	0.88	0.82	-0.09	0.44	0.83	0.74
Operating income	0.85	0.75	-0.08	0.37	0.79	0.70
Total assets	0.88	0.69	-0.06	0.42	0.86	0.70
Own funds requirement operational risk	0.89	0.82	-0.07	0.51	0.83	0.84
Own funds requirement market risk	0.71	0.64	-0.10	0.39	0.59	0.61

Cross Section Analysis

- Cross Section Analysis shows a high dependence of frequency to bank variables
- Total losses (as a result) as well
- OpRisk RWA do a relatively good job (both in terms of linear and rank correlation)
- Mean losses exhibit negative empirical linear correlation coefficients with financial indicators in our database. Rank correlation which is less sensitive to outliers also shows positive but moderate correlation for the mean loss



Parametric Distributions

- For risk quantification, the part that mainly matters is the **tail of the severity distribution**
- This is – by definition – the area where there is little data
- Theoretical distributions are crucial to better describe the tail
- To maintain enough data points we have to pool the data across banks
- An alternative approach would be to pool across ET and BL, but this would still mean too few observations for some banks and statistical methods
- Results obtained in the first data exploration and in the cross-section analysis suggest that across bank heterogeneity (with regards to size) seems to be less pronounced than the cross ET or BL heterogeneity
- Which distribution fits best?
  - Moscadelli (2004) or Dutta and Perry (2006) fit a range of parametric distributions to collected operational loss data
  - We will focus on (i) the generalized Pareto distribution (ii) the g-and h-distribution and (iii) the modified Champernowne distribution, and – for comparison purpose – lognormal and exponential

(1) The generalized Pareto distribution

- Builds on famous theorem of Pickands, Balkema and de Haan, also called the theorem of extreme value theory:

"nearly every tail (=distribution function above certain threshold u) converges to one that can be depicted by"

$$GPD_{\beta,\xi}(x) = \begin{cases} 1 - (1 + \xi x/\beta)^{-1/\xi} & \xi \neq 0 \\ 1 - \exp(-x/\beta), & \xi = 0 \end{cases}$$

- $\hat{\beta}$ and $\hat{\xi}$ by numerically maximizing the log-likelihood,

$$\ln L(\beta, \xi; X_1, \dots, X_n) = \sum_{j=1}^{n} \ln gpd_{\beta,\xi}(X_n)$$

$$= -n \ln \beta - \left(1 + \frac{1}{\xi}\right) \sum_{j=1}^{n} \ln\left(1 + \xi \frac{X_j}{\beta}\right)$$

- Fitting $\hat{\beta}$ and $\hat{\xi}$ is straightforward. More complicated is the choice of the threshold u

(2) g- and h- distribution

- Transformation of the standard normal random variable Z

$$Y_{g,h}(Z) = (\exp(gZ) - 1)\frac{\exp\,(hZ^2/2)}{g}$$

- Dutta and Perry (2006) introduce the scale parameter B and the location parameter A and define $X_{g,h}(Z) := A + B\, Y_{g,h}(Z)$
- Lacking an explicit density function
- Estimation procedure described first in Hoaglin (1985)

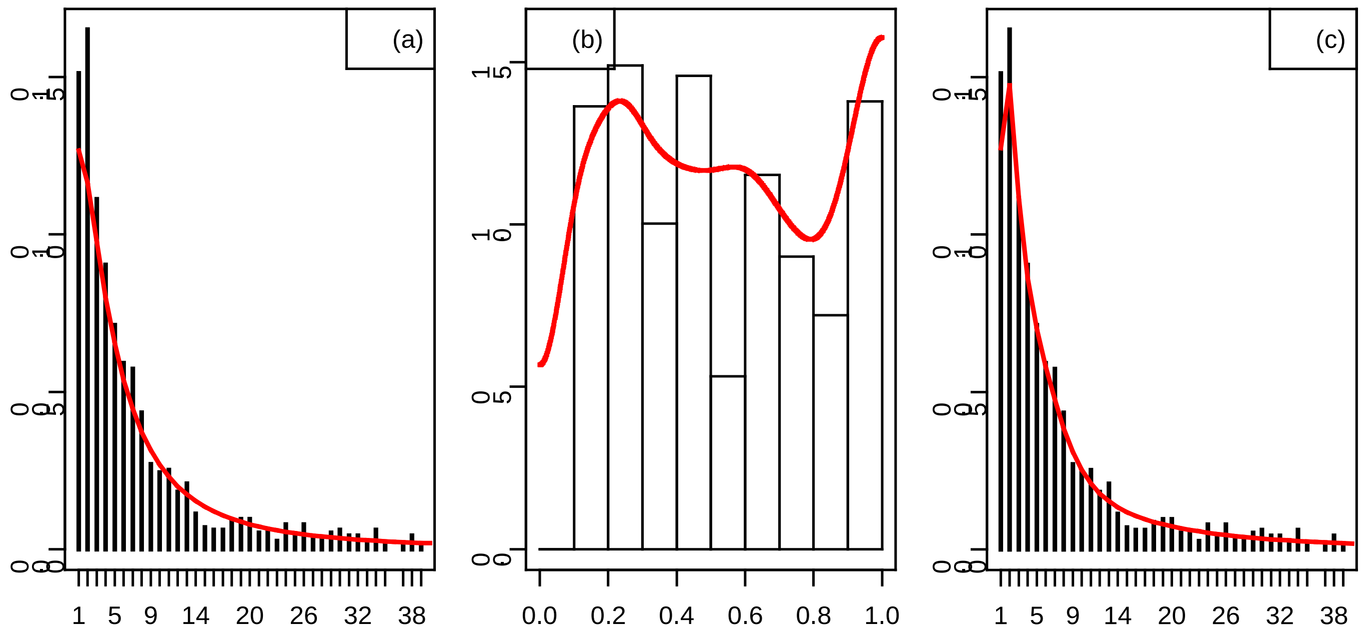
(3) Modified Champernowne function

- Proposed first by Buch-Larsen et al. (2005)
- Semi-parametric approach, consisting of 3 steps
- Tries to exploit the flexibility of kernel density estimation with the merits of the Modified Champernowne distribution function

$$T_{\alpha,M,c}(x) = \frac{(x+c)^{\alpha}}{(x+c)^{\alpha} + (M+c)^{\alpha} - 2c^{\alpha}}$$

- M corresponds to the median of each dataset
- Parameter c has scale and shape properties depending on α. When $\alpha < 1$ higher values of c result in lighter tails and heavier tails when $\alpha > 1$. Moreover, when there is a mode ($\alpha > 1$) higher values of c shifts it to the left

(3) Modified Champernowne function – steps of estimation



- (a) raw data in black and estimated modified Champernowne distribution in red
- (b) data transformed via cdf and kernel density estimator in red and
- (c) back-transformed kernel density in red and (again) raw data in black
- Applied to data of the BL “asset management”.

Cross Validation Exercise

Per BL and ET:

(I) We randomly split the observations in 85% training set and 15% validation set

(II) We randomly draw observations from the training set with replacement as many times as the original number of observations of the ET or BL category. Therefore, each method starts from the same number of observations as in the original fitting above

(III) Based on this sample we fit a GPD, a g- and h- distribution, a density via the Champernowne Approach plus lognormal and exponential

(IV) We compare the log-likelihood of the validation set for all fitted distributions. This gives us a performance indicator of each approach for one cross validation run, which we use to rank them

- We run the steps (I) to (IV) 5000 times

Results of the Cross Validation Exercise

- Best and second best performer highlighted

EVENT TYPES	GPD	g and h	mod.Champ.	Exponential	LogNorm
internal fraud, n=2,002					
mean rank	**1.90**	2.51	**2.06**	4.79	3.75
external fraud, n=18,598					
mean rank	**1.54**	**2.27**	2.99	4.79	3.41
employment practices & workplace safety, n=855					
mean rank	**2.22**	3.31	3.36	4.41	**1.70**
clients, products & business practices, n=5,537					
mean rank	**1.70**	**2.11**	3.81	4.80	2.58
damage to physical assets, n=2,631					
mean rank	**1.13**	**2.09**	3.30	4.61	3.87
business disruption & system failures, n=1,291					
mean rank	**1.98**	**1.96**	3.85	4.59	2.61
execution, delivery & process management, n=10,611					
mean rank	**1.44**	2.64	4.08	4.85	**1.99**

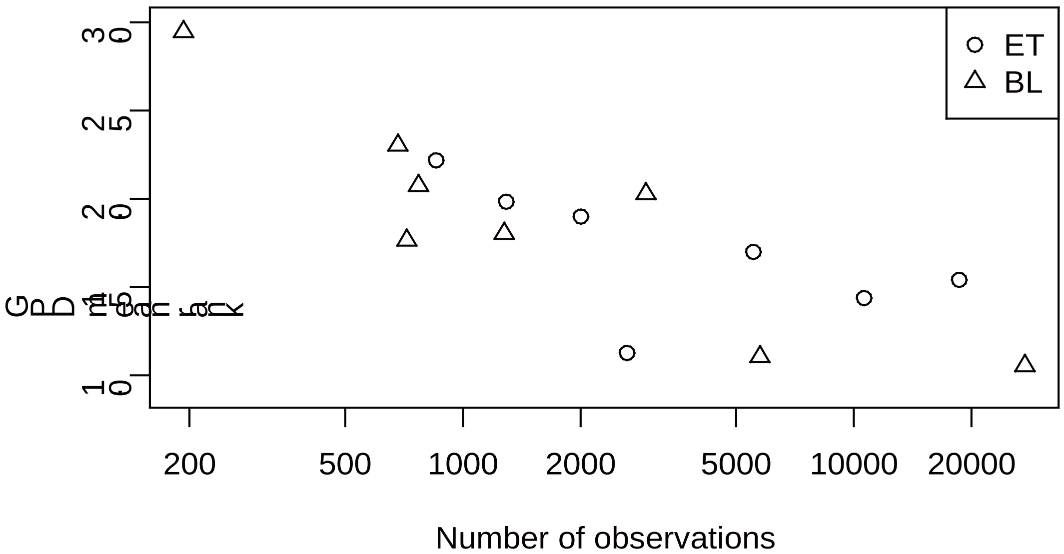
BUSINESS LINES	GPD	g and h	mod.Champ.	Exponential	LogNorm
corporate finance, n=770					
mean rank	**2.07**	2.51	**2.15**	4.59	3.67
trading & sales, n=2,941					
mean rank	**2.03**	2.87	**2.46**	4.87	2.77
retail banking, n=719					
mean rank	**1.77**	2.73	3.62	4.56	**2.33**
commercial banking, n=5,751					
mean rank	**1.10**	**2.15**	3.17	4.79	3.79
payment & settlement, n=27,386					
mean rank	**1.05**	3.10	4.15	4.70	**2.00**
agency services , n=682					
mean rank	**2.30**	2.65	3.69	4.24	**2.12**
asset management, n=1,276					
mean rank	**1.80**	3.06	3.65	4.68	**1.81**
retail brokerage, n=194					
mean rank	2.95	**2.60**	2.89	3.69	**2.88**

Results

- In all categories the exponential distribution has the lowest mean rank. This confirms prior research that the exponential distribution is not able to capture operational risk characteristics well in the tail
- Out of the 7 ET and 8 BL considered the GDP is only in the BL “retail brokerage” not among the top two
- Additionally, the GPD impresses by ranking hardly ever last in the comparison to the others. The GPD’s highest percentage of last ranks (with exception of retail brokerage) is 12% in the BL “agency services”, still significantly below the 20% which would be expected under the hypothesis of equal performance

Results

- We find obvious negative dependence of the GPD performance *relative* to the others' on the number of observations in each category



- Interestingly, we find that several GPD distributions fitted (for some BL and ET) show a parameter $\hat{\xi}$ statistically significantly greater than 1. This implies infinite mean (and variance)

Conclusions

- Frequency of losses across business lines (BL) and event types (ET) is quite heterogeneous
- Cross-section:
  - operational risk RWA seem to be the best indicator for frequency and also for total loss among the considered indicators. Also, it is interesting to note that in our dataset mean losses are not linearly correlated with banks' size
- Cross Validation of Severity Distributions:
  - confirm the finding of prior research that the GPD is among the best choices in all but one ET and BL. Furthermore, the g- and h- distribution performs very well in fitting operational losses followed by – surprisingly – the relatively simple lognormal distribution
  - the *relative* performance of the GPD compared to other approaches depends strongly on the number of observations