The application of a probabilistic catastrophe risk modelling framework to poverty outcomes:

General form vulnerability functions relating household poverty outcomes to hazard intensity in Ethiopia

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HERIOT WATT UNIVERSITY

Summary of research activities

- We bring together two strands of research that have thus far been developed independently:
    - Catastrophe risk modelling
    - Economic analysis of vulnerability to poverty.
- The aim is to determine the validity/viability of applying a derived set of damage (vulnerability) functions based on realized shocks and household expenditure/consumption outcomes, onto a forward-looking view of drought risk.
- We outline the contribution that combining the two analyses can bring, show preliminary results and outline future plans

- Q: Can the results be generalized/validated "enough" to bolt on to the flexible drought risk model?

Summary of Findings

- We test several models linking consumption to a covariate shock, drought
- Results show (fairly) consistent results: stable relationship
- Test for several different heterogeneous impacts
- Non-linearity tested and quadratic model appears to perform best
- Statistical learning does not show great differences between models nor affected by choice of training/testing dataset when “sliced”
- Results less encouraging for 2012 unrelated data
- Simulated poverty impacts we can be fairly confident about – confidence falls above 50% crop loss?

Outline of presentation

- CAT risk modelling
- Microeconomic studies of shock impact/vulnerability
- Outline regression model
- Statistical learning – stress testing the model
- Putting the two together: poverty impacts of drought scenarios
- Caveats: mainly data on extreme events
- Next steps: Full CAT risk model?

Probabilistic Catastrophe Risk (CAT Risk) Models

- Frequently relied upon in international insurance markets
- Develop a view of risk beyond the historical occurrence of catastrophes, for calculation of potential future impacts
- Consider an extensive range of possible event scenarios well beyond the historical record
- Primarily developed to output risk in financial terms
- Potential to use them to support disaster risk management more broadly has been recognized in schemes such as the Pacific Risk Information System, CAPRA Program and Africa RiskView platform.
- Thus far – CAT risk models have not been used to estimate likely poverty/welfare consequences of disaster risk at household level

Microeconomic analysis of shocks (natural disasters)

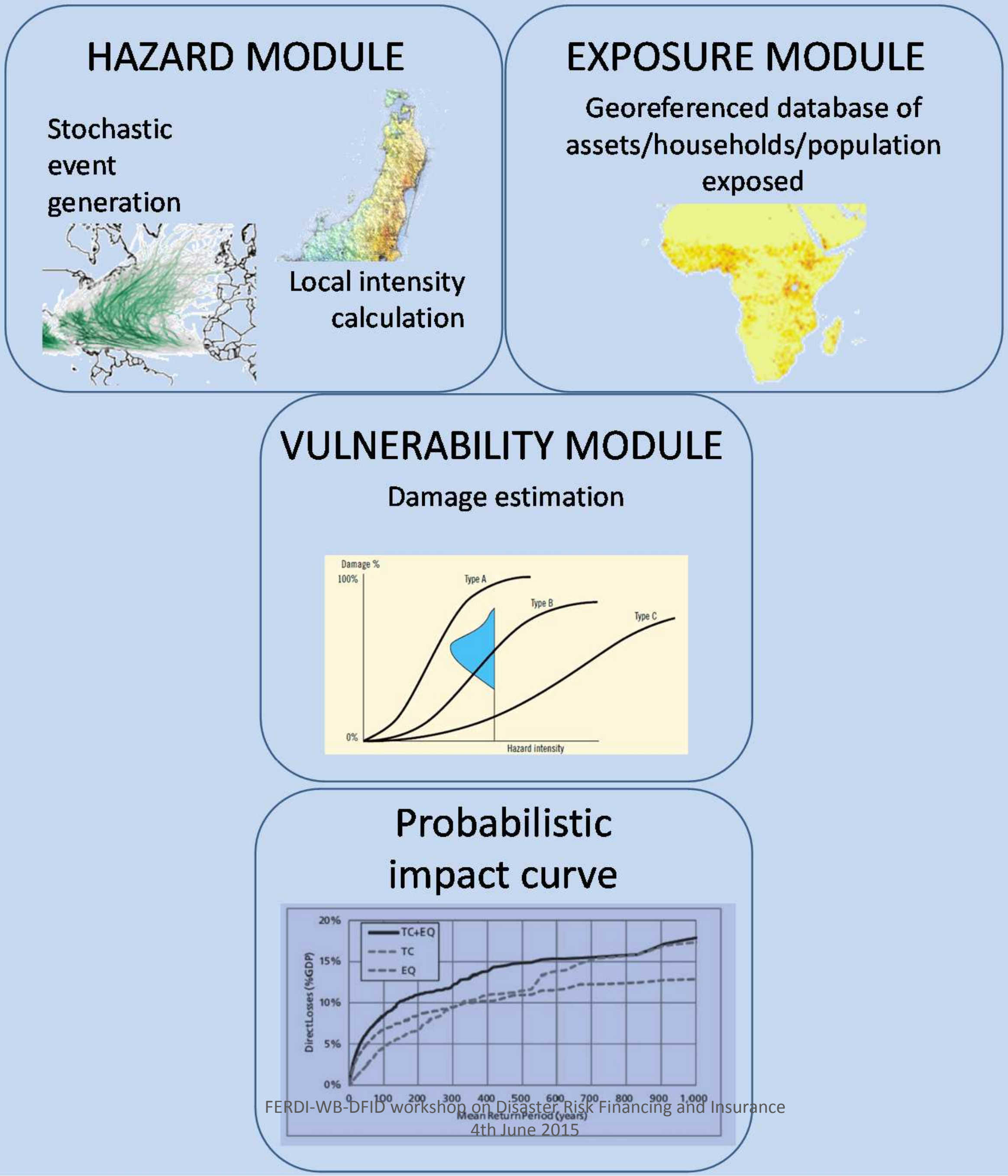
- Body of evidence has consolidated past 10 years: micro studies on extreme events– drought, earthquake, flood, epidemic
- Evaluate ex-post impact of realized shock on welfare outcomes
  - Consumption/Expenditure
  - Child health (height)
  - Asset selling, child labor and other coping responses
- Short and Long-term studies
- Also evidence on smaller fluctuations mattering
- More sparce: forward looking studies, conceptual analysis of vulnerability
- *Ex-ante* analysis of potential poverty impacts for shocks

CAT Risk meets microeconomics

- Typical in vulnerability literature “ideally we would need information on the ex-ante distribution of future consumption outcomes and their probability” (e.g. Hill and Porter 2013)

- If economists develop an externally valid model of shock impact on welfare across the distribution of the shock…
- If CAT risk model can simulate probability and severity of shock…
- Powerful combination for assessing future needs

Box 1.1: Probabilistic Catastrophe Risk Modelling Frameworks



Example: modelling process for a building exposed to earthquake

In a probabilistic earthquake model, possible financial loss to an insurance company underwriting a policy for a particular building would be determined as follows:

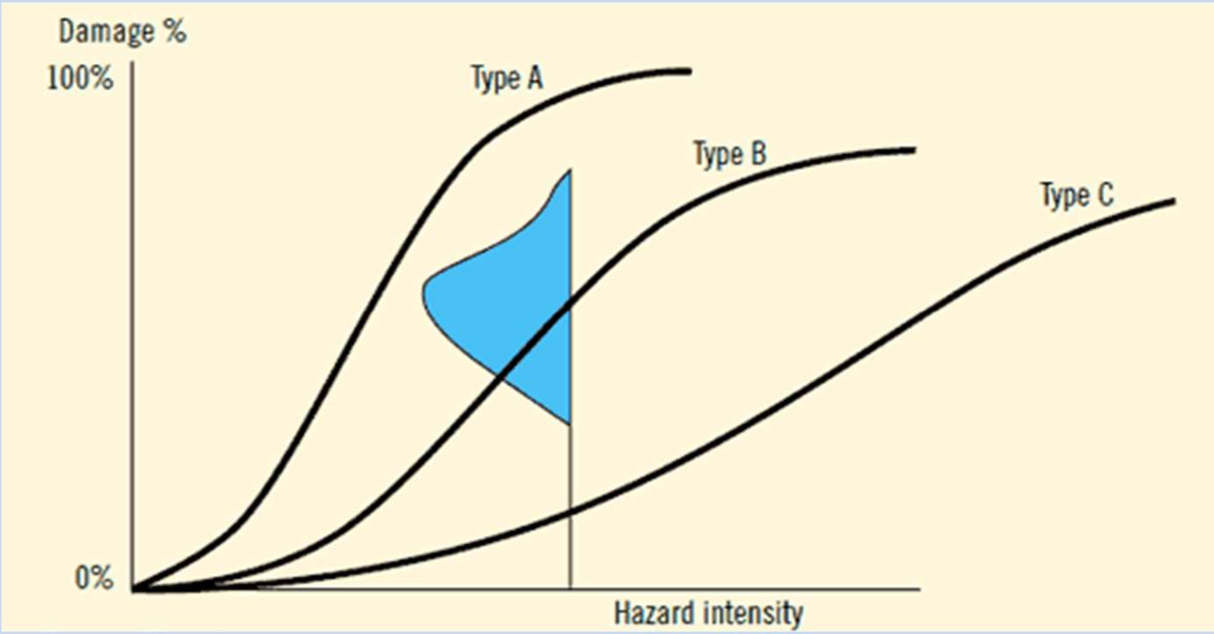
1) The **hazard** component: how severe? Spectral acceleration, based on tens of thousands of different modelled stochastic events taking into account factors such as the size of the earthquake, its location relative to the building, and local conditions such as soil;

2) The resulting **damage** experienced by the building would next be determined based on the level of hazard (spectral acceleration) and the physical building characteristics that determine vulnerability, such as building material, number of stories and year of build;

3) The level of damage of the building is converted into a <u>total financial loss</u> based on factors such as replacement value, and the policy conditions such as deductible and limit are applied to give the insurance company's perspective.

VULNERABILITY MODULE

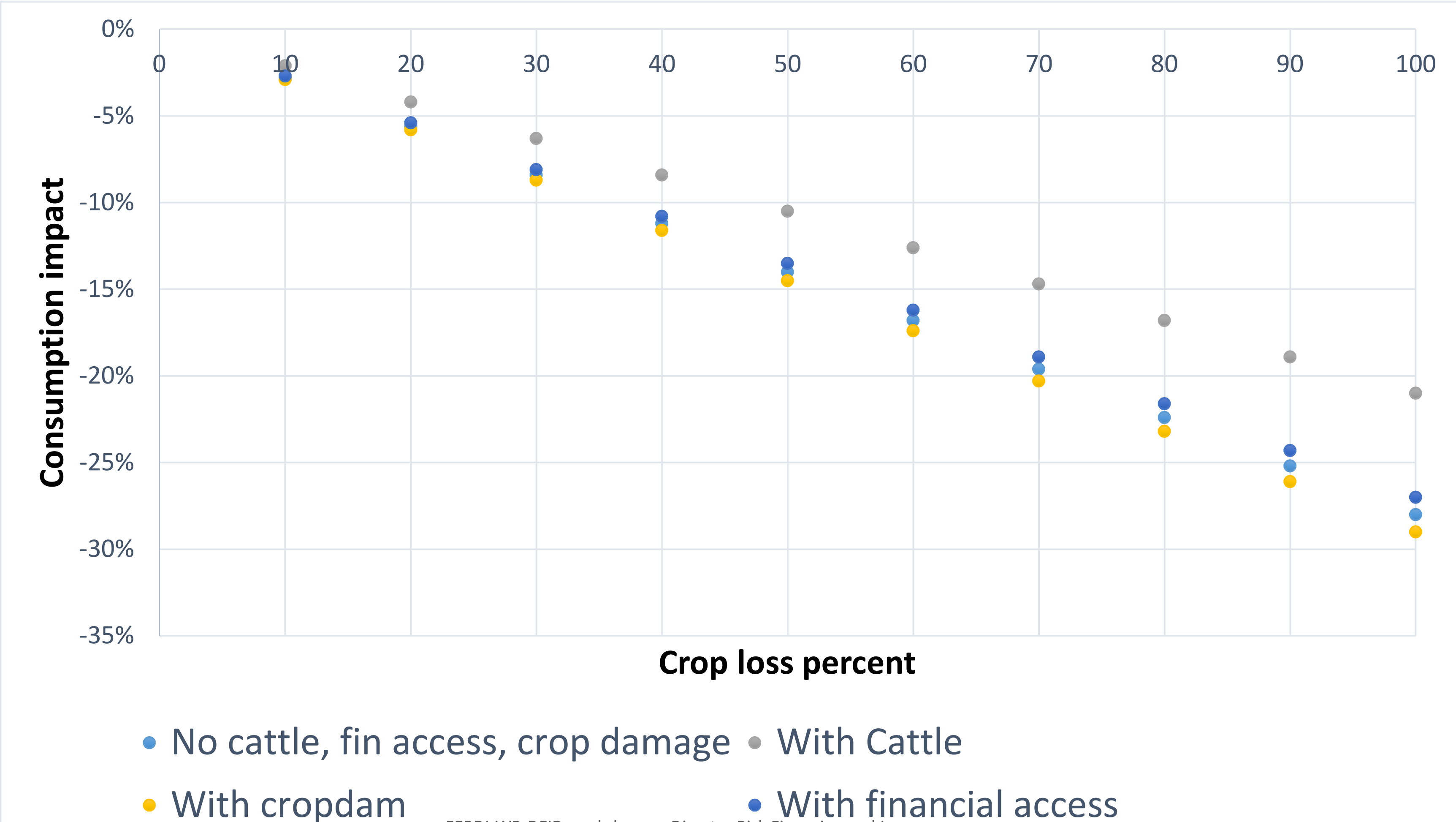
Damage estimation



Modelling process for a household exposed to drought

1) The hazard component is a (ex-post) index of drought (crop yield shortfall). How severe depends on geographic characteristics and rainfall model.
2) The resulting damage is determined based on the level of the hazard (community-specific crop loss) and characteristics of the household that mitigate or amplify the impact of the shock.
3) The total financial loss can be conceptualized e.g. as the poverty gap of the household – the shortfall of expected household consumption from the poverty line (summed across all households)

Vulnerability module: Crop loss and consumption



Next

- Present the model and assumptions
- Tradeoff between well-fitting model and over-fitting

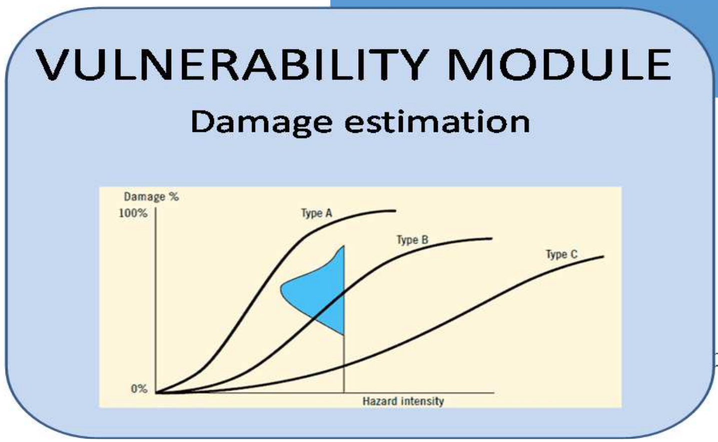
Key issues:

- Internal validity
- External validity (out of sample predictions in particular)

Establishing the relationship between consumption and drought

- Regressions based on initial work by Hill and Porter (2014) that derived a general model of consumption for Ethiopian households using rural and urban, and simulated impact of drought, food prices, and other idiosyncratic shocks on (ln) consumption per adult.
- We drop urban and pastoral hh
- Include higher powers of the drought shock (squared, cubed) to capture non-linearities especially for higher values of drought
- Include interaction terms in order to capture the “types” for the vulnerability module (heterogeneity of impact for economists)

Household characteristics	Interacting variables
Ability of head to access coping strategies	Head education level, sector of occupation, gender
Household composition that allows labour response	Dependency ratio, ratio of able-bodied
Household assets that mitigate shock	Cattle, other livestock, jewelry
Other shocks that compromise ability to mitigate shock	Illness, livestock disease, crop damage from pests
Access to institutional coping strategies	Distance to market, access to financial products (insurance, credit), public safety net access.



Data

- 2005 and 2011 rounds of the nationally representative Household Income and Consumption Expenditure and Welfare Monitoring Surveys (HICES/WMS) (17,134 observations in total)
- Household consumption per adult equivalent, hh characteristics, self-reported shocks, whether received PSNP income in 2011.
- Merge with the LEAP historical crop loss data taken from the World Food Programme's LEAP (Livelihoods Early Assessment and Protection) software.
  - Uses time-variable meteorological recordings combined with data tables on soil and crop characteristics to calculate yield reductions relative to the expected production under non-limiting water conditions.

Descriptive Statistics

Variable	2005	2011
Ln adult monthly expend	7.27	7.28
	(0.50)	(0.50)
LEAP crop loss	16.33	11.58
	(18.53)	(13.25)
Femalehead	0.23	0.23
	(0.42)	(0.42)
Age hhead	43.24	44.43
	(15.73)	(15.74)
Head school	0.25	0.30
	(0.43)	(0.46)
Cattle	0.66	0.67
	(0.47)	(0.47)
Financial access	0.25	0.50
	(0.43)	(0.50)
Distance to town	326.83	378.64
	(229.93)	(285.74)
Dependency ratio	0.49	0.50
	(0.24)	(0.23)
Death shock	0.08	0.02
	(0.27)	(0.13)
illness shock	0.23	0.08
	(0.42)	(0.27)
cropdamage shock	0.10	0.03
	(0.30)	(0.17)
livshock shock	0.09	0.05
	(0.29)	(0.21)
jobloss shock	0.01	0.00
	(0.09)	(0.04)
Prices hock	0.02	0.18
	(0.14)	(0.38)
Psnp beneficiary	0.00	0.15
	(0.00)	(0.36)
highlandsd rought	0.39	0.37
	(0.49)	(0.48)
highlands reliable	0.38	0.34
	(0.48)	(0.47)
lowlands reliable	0.03	0.11
	(0.18)	(0.3)1
lowlands enset	0.19	0.18
	(0.40)	(0.39)
Good roof	0.22	0.34
	(0.42)	(0.47)
Hhsize	4.91	5.00
	(2.28)	(2.20)

Results

	Baseline	Model 1	Model 2	Model 3	Model 4
(Intercept)	7.794^{***}	7.800^{***}	7.769^{***}	7.775^{***}	7.765^{***}
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
cropleap	-0.015^{***}	-0.020^{***}	-0.020^{**}	-0.025^{***}	-0.048^{***}
	(0.002)	(0.003)	(0.006)	(0.007)	(0.007)
boot.se	0.0025	0.0030	0.0065	0.0137	0.0162
boot.ci	(-0.020, -0.0104)	(-0.0256,-0.0139)	(-0.0322, -0.0069)	(0.0260, 0.0798)	(-0.0181, 0.0455
Dr hschool		0.004	0.004	0.003	0.001
		(0.005)	(0.005)	(0.005)	(0.005)
Dr femalehead		0.002			
		(0.005)			
Dr psnpb		0.053^{***}	0.053^{***}	0.050^{***}	0.053^{***}
		(0.010)	(0.010)	(0.010)	(0.010)
Dr cattle			-0.007^{*}	-0.007^{*}	-0.005
			(0.003)	(0.003)	(0.003)
Dr notag			0.007	0.006	0.006
			(0.006)	(0.006)	(0.006)
Dr disttown07			-0.000	0.000	0.000^{***}
			(0.000)	(0.000)	(0.000)
Dr dependency			0.006	0.007	0.008
			(0.009)	(0.009)	(0.009)
Dr finaccess				0.014^{**}	0.012^{*}
				(0.005)	(0.005)
Dr illness				0.006	0.006
				(0.006)	(0.006)
Dr cropdam				-0.015^{*}	-0.015^{*}
				(0.007)	(0.007)
Dr livshock				-0.003	-0.001
				(0.007)	(0.007)
Dr highlands reliable					0.047^{***}
					(0.006)
Dr lowlands reliable					-0.029^{**}
					(0.011)
Dr lowlands enset					0.033^{**}
					(0.010)
R^2	0.245	0.246	0.247	0.247	0.251
Adj. R^2	0.244	0.245	0.245	0.246	0.249
AIC	20047.21	20022.04	20072.26	20065.60	20001.73
BIC	20271.92	20270.00	20335.72	20360.06	20319.43
Num. obs.	17134	17134	17134	17134	17134

Results

No interactions

	Baseline	Model 1	Model 2	Model 3	Model 4
(Intercept)	7.794***	7.800***	7.769***	7.775***	7.765***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
cropleap	−0.015***	−0.020***	−0.020**	−0.025***	−0.048***
	(0.002)	(0.003)	(0.006)	(0.007)	(0.007)
boot.se	0.0025	0.0030	0.0065	0.0137	0.0162
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Dr hschool		0.004	0.004	0.003	0.001
		(0.005)	(0.005)	(0.005)	(0.005)
Dr femalehead		0.002			
		(0.005)			
Dr psnpb		0.053***	0.053***	0.050***	0.053***
		(0.010)	(0.010)	(0.010)	(0.010)
Dr cattle			−0.007*	−0.007*	−0.005
			(0.003)	(0.003)	(0.003)
Dr notag			0.007	0.006	0.006
			(0.006)	(0.006)	(0.006)
Dr disttown07			−0.000	0.000	0.000***
			(0.000)	(0.000)	(0.000)
Dr dependency			0.006	0.007	0.008
			(0.009)	(0.009)	(0.009)
Dr finaccess				0.014**	0.012*
				(0.005)	(0.005)
Dr illness				0.006	0.006
				(0.006)	(0.006)
Dr cropdam				−0.015*	−0.015*
				(0.007)	(0.007)
Dr livshock				−0.003	−0.001
				(0.007)	(0.007)
Dr highlands reliable					0.047***
					(0.006)
Dr lowlands reliable					−0.029**
					(0.011)
Dr lowlands enset					0.033**
					(0.010)
R^2	0.245	0.246	0.247	0.247	0.251
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BIC	20271.92	20270.00	20335.72	20360.06	20319.43
Num. obs.	17134	17134	17134	17134	17134

Results

Parsimonious model

	Baseline	Model 1	Model 2	Model 3	Model 4
(Intercept)	7.794***	7.800***	7.769***	7.775***	7.765***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
cropleap	−0.015***	−0.020***	−0.020**	−0.025***	−0.048***
	(0.002)	(0.003)	(0.006)	(0.007)	(0.007)
boot.se	0.0025	0.0030	0.0065	0.0137	0.0162
boot.ci	(-0.020, -0.0104)	(-0.0256,-0.0139)	(-0.0322, -0.0069)	(0.0260, 0.0798)	(-0.0181, 0.0455
Dr hschool		0.004	0.004	0.003	0.001
		(0.005)	(0.005)	(0.005)	(0.005)
Dr femalehead		0.002			
		(0.005)			
Dr psnpb		0.053***	0.053***	0.050***	0.053***
		(0.010)	(0.010)	(0.010)	(0.010)
Dr cattle			−0.007*	−0.007*	−0.005
			(0.003)	(0.003)	(0.003)
Dr notag			0.007	0.006	0.006
			(0.006)	(0.006)	(0.006)
Dr disttown07			−0.000	0.000	0.000***
			(0.000)	(0.000)	(0.000)
Dr dependency			0.006	0.007	0.008
			(0.009)	(0.009)	(0.009)
Dr finaccess				0.014**	0.012*
				(0.005)	(0.005)
Dr illness				0.006	0.006
				(0.006)	(0.006)
Dr cropdam				−0.015*	−0.015*
				(0.007)	(0.007)
Dr livshock				−0.003	−0.001
				(0.007)	(0.007)
Dr highlands reliable					0.047***
					(0.006)
Dr lowlands reliable					−0.029**
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Dr lowlands enset					0.033**
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BIC	20271.92	20270.00	20335.72	20360.06	20319.43
Num. obs.	17134	17134	17134	17134	17134

Results

Exogenous interactions

	Baseline	Model 1	Model 2	Model 3	Model 4
(Intercept)	7.794***	7.800***	7.769***	7.775***	7.765***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
cropleap	−0.015***	−0.020***	−0.020**	−0.025***	−0.048***
	(0.002)	(0.003)	(0.006)	(0.007)	(0.007)
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boot.ci	(-0.020, -0.0104)	(-0.0256,-0.0139)	(-0.0322, -0.0069)	(0.0260, 0.0798)	(-0.0181, 0.0455
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		(0.005)	(0.005)	(0.005)	(0.005)
Dr femalehead		0.002			
		(0.005)			
Dr psnpb		0.053***	0.053***	0.050***	0.053***
		(0.010)	(0.010)	(0.010)	(0.010)
Dr cattle			−0.007*	−0.007*	−0.005
			(0.003)	(0.003)	(0.003)
Dr notag			0.007	0.006	0.006
			(0.006)	(0.006)	(0.006)
Dr disttown07			−0.000	0.000	0.000***
			(0.000)	(0.000)	(0.000)
Dr dependency			0.006	0.007	0.008
			(0.009)	(0.009)	(0.009)
Dr finaccess				0.014**	0.012*
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Dr illness				0.006	0.006
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Full interactions

Results

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Results

Plus regional interactions

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Dr femalehead		0.002			
		(0.005)			
Dr psnpb		0.053***	0.053***	0.050***	0.053***
		(0.010)	(0.010)	(0.010)	(0.010)
Dr cattle			−0.007*	−0.007*	−0.005
			(0.003)	(0.003)	(0.003)
Dr notag			0.007	0.006	0.006
			(0.006)	(0.006)	(0.006)
Dr disttown07			−0.000	0.000	0.000***
			(0.000)	(0.000)	(0.000)
Dr dependency			0.006	0.007	0.008
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Results summary

- Drought shock fairly stable impact across models: approx 2% fall in consumption for 10% crop loss (base household)
- Cattle owners impact is less (unsurprising)
- PSNP consistently mitigates the impact
- Crop damage (self-reported) exacerbates impact

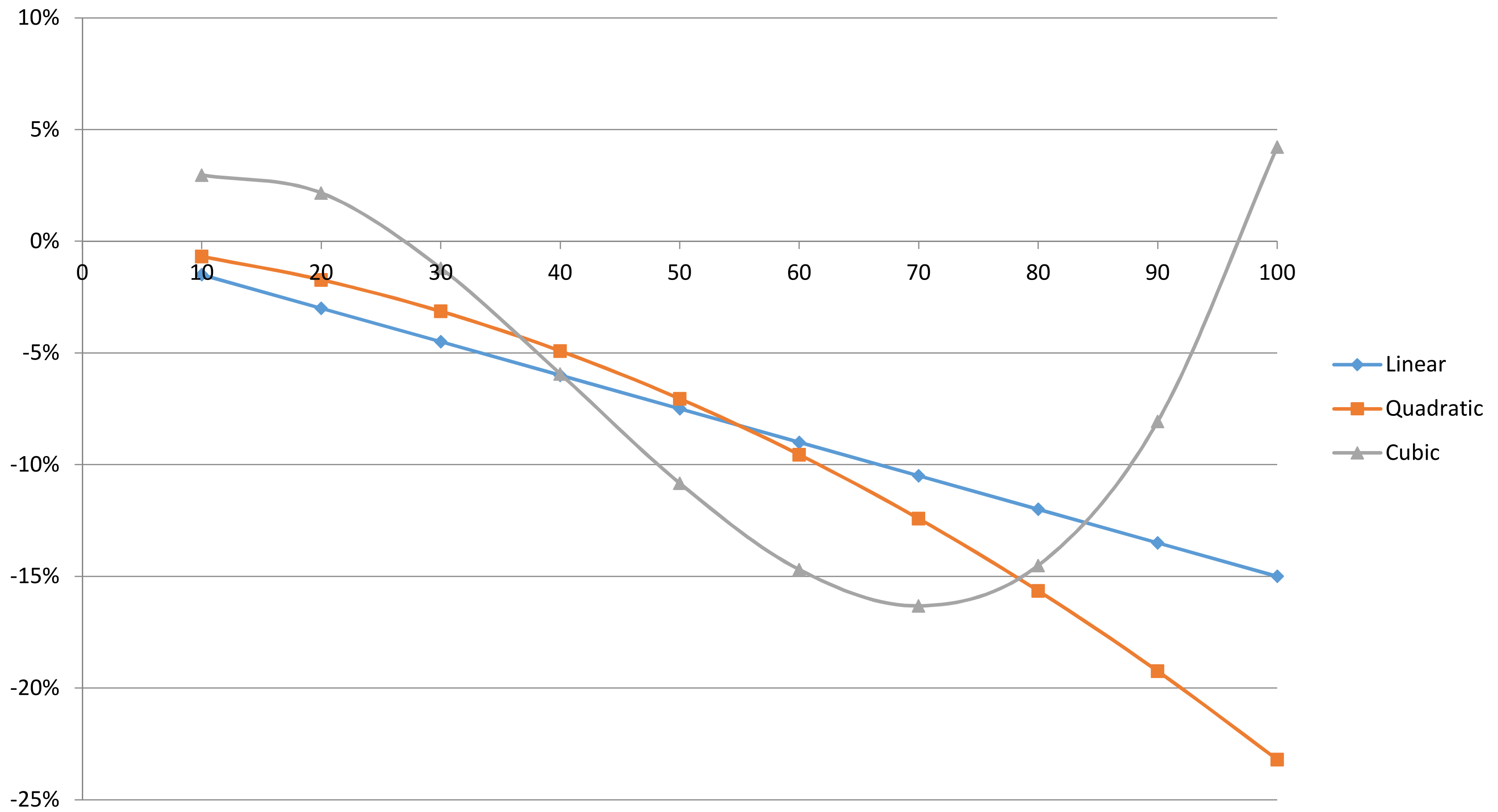
- Geographic differences shock: impact worst in lowlands reliable, highlands drought prone, lowlands enset, highlands reliable.

- Some support of a quadratic model (data paucity/support though)

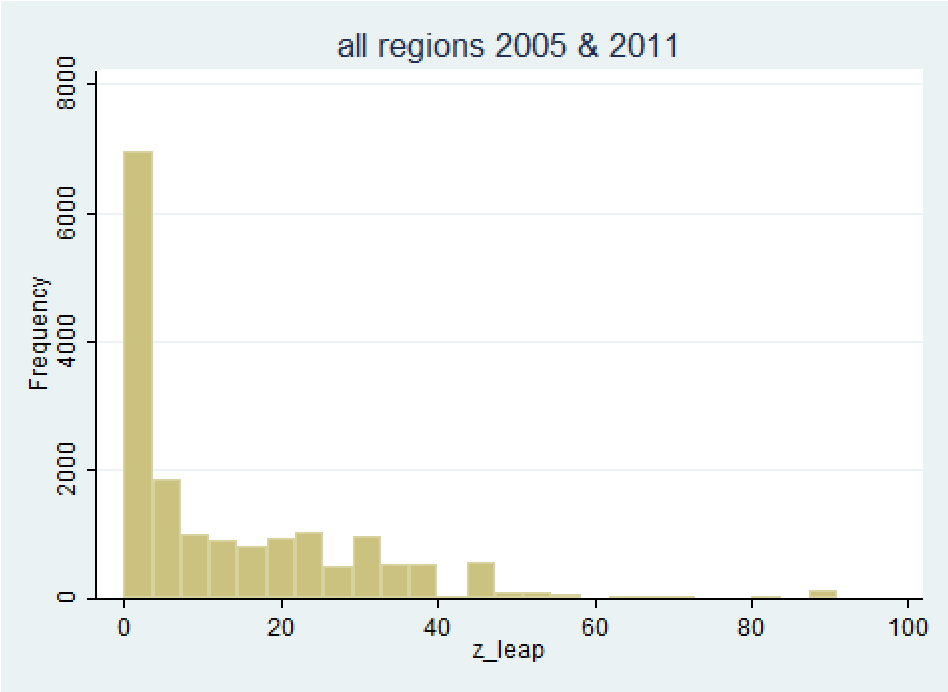
Caveats

- Measurement error
- Panel data and unobserved household/community characteristics? Tradeoff between nationally representative and panel
- Data Scarcity above the 50% drought loss mark
- E.g. Using Panel data (ERHS) Porter 2012 found non-linear impact of drought: bottom quintile of the (local) rainfall distribution led to consumption drop of 20%

Comparison of non-linear models



Frequency and 5% bin of Drought-Crop-Loss Data (LEAP)



Validity - concepts

- Internal validity (identification): How do we know we are capturing the true impact of the crop loss on consumption? (Antilla-Hughes & Sharma, 2013)
  - Weather shocks are exogenous but still could be correlated with average income
  - Panel data preferred
- External validity:
  - Out of Sample (higher drought)
  - Across Ethiopian Agro-Climactic Zones
  - Across time

- To establish external validity of any statistical results across time and contexts beyond reasonable doubt, it would be necessary to conduct identical analysis many times (replication) and then derive bounds for the relationships. This is not possible in the timeframe of the initial analysis, but has potential for future exercise?
- Validate results across as many countries and time periods as data permit.

Statistical Learning

- We want to fit model well but avoid overfitting
- We want to test the predictive power of the vulnerability relationships
- Use Statistical Learning Methods of re-sampling and cross-validation (James et al, 2013).
- K-fold Cross validation: randomly divide the data into training and testing datasets, and check performance of the model using Mean Squared Error.

- We also compare the bootstrap estimates of the drought parameter across all models.
- Precedents in Economics:
  - Todd & Wolpin –Racial Score Gaps (2009)
  - Athey & Imbens – machine learning methods for heterogeneity (2015)
  - Poverty scorecard project (e.g. Skoufias, 2015)

Testing the models with 2005 and 2011 as training and “holdout” data

	Baseline	Model 1	Model 2	Model 3	Model 4
Original R^2	0.245	0.246	0.247	0.247	0.251
Original Adj. R^2	0.244	0.245	0.245	0.246	0.249
Original AIC	20047.21	20022.04	20072.26	20065.60	20001.73
Original BIC	20271.92	20270.00	20335.72	20360.06	20319.43
Num. obs.	17134	17134	17134	17134	17134
boot.cv	0.170	0.171	0.170	0.170	**0.169**
RMSEtest05	**0.023**	0.0281	0.0338	0.0272	0.0291
RMSEtest11	0.0438	0.0431	**0.042**	0.0429	0.0490

Notes: cv=cross-validation, R2=r-squared; AIC=Aikike information Criterion; BIC= ; boot=bootstrap; RMSE=root mean squared error.

Take home points

- In all the “cuts” of the data, the differences in MSE both of models and of choice in training/testing data are very small…

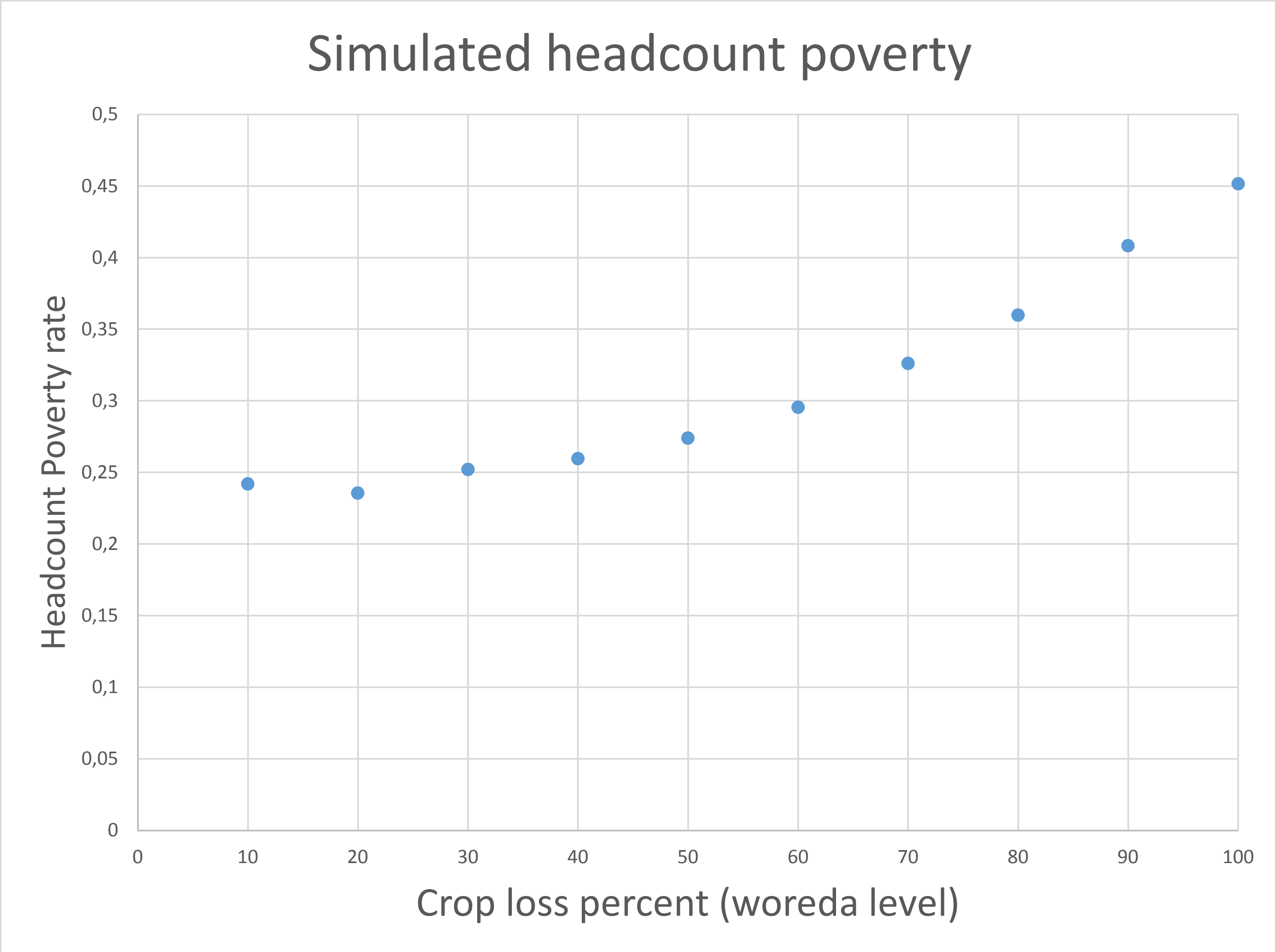
- When 2005 is the training dataset, Model 2 (parsimonious) is the best predictor (lowest MSE).
- However when 2011 is the training dataset, the baseline model performs best.
- Quadratic model overall performs best when 2011 is testing dataset (but not when 2005 is testing dataset).
- Regional: Highlands drought prone as testing region has higher MSE

- 2011 performs better as a training dataset for 2005 than vice-versa?

Testing the model on 2012 data

- Ethiopian Rural Socioeconomic Survey 2012
- Smaller survey (4000 hh)
- Comparability of Questionnaire/timing? (e.g. recall for consumption)
- Not nationally representative (tho representative of larger 4 regions)

- Statistical learning:
  - MSE is much higher (tenfold) than on the cross-validation 2005-2011
  - Differences between models is again very small though
  - 2005 performs better as a training dataset for 2012 than 2011 does
  - Best fit model is quadratic, with full interaction terms including region interactions


Simulated headcount poverty
Headcount Poverty rate
0,5
0,45
0,4
0,35
0,3
0,25
0,2
0,15
0,1
0,05
0
0
10
20
30
40
50
60
70
80
90
100
Crop loss percent (woreda level)

Extensions

- From Headcount to Poverty Gap allows full analysis of full fiscal costs of poverty gap
- Building the full CAT risk model to “bolt-on” to the impacts
- Build in macroeconomic effects of covariate shocks
- Lagged shocks or multiplicative shock impacts

- Further stress testing of model?
  - Higher levels of drought?
  - Panel data (not nationally representative)?
  - Woreda level analysis of poverty rates and drought

Summary

Aim: to explore whether it is possible to combine a regression-based model of shocks and consumption (ex-post) impacts with an ex-ante CAT risk model

Results do show quite stable model within the 2005-2011 data, less so for 2012 (but data compatibility?)

Key challenge – stability of the model over extreme events that are impossible to model econometrically based on existing data

Comments most welcome

References

- Anttila -Hughes and Sharma (2014) Linking Risk Models to Microeconomic Indicators, World Bank publications, 2014.
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- Todd, Petra E., and Kenneth I. Wolpin. "The production of cognitive achievement in children: Home, school, and racial test score gaps." *Journal of Human capital* 1.1 (2007): 91-136.