Anders Persson’s Moscow seminars 17 May 2016

1. **Decision making from probability forecasts** –*turning a weakness into a strength*

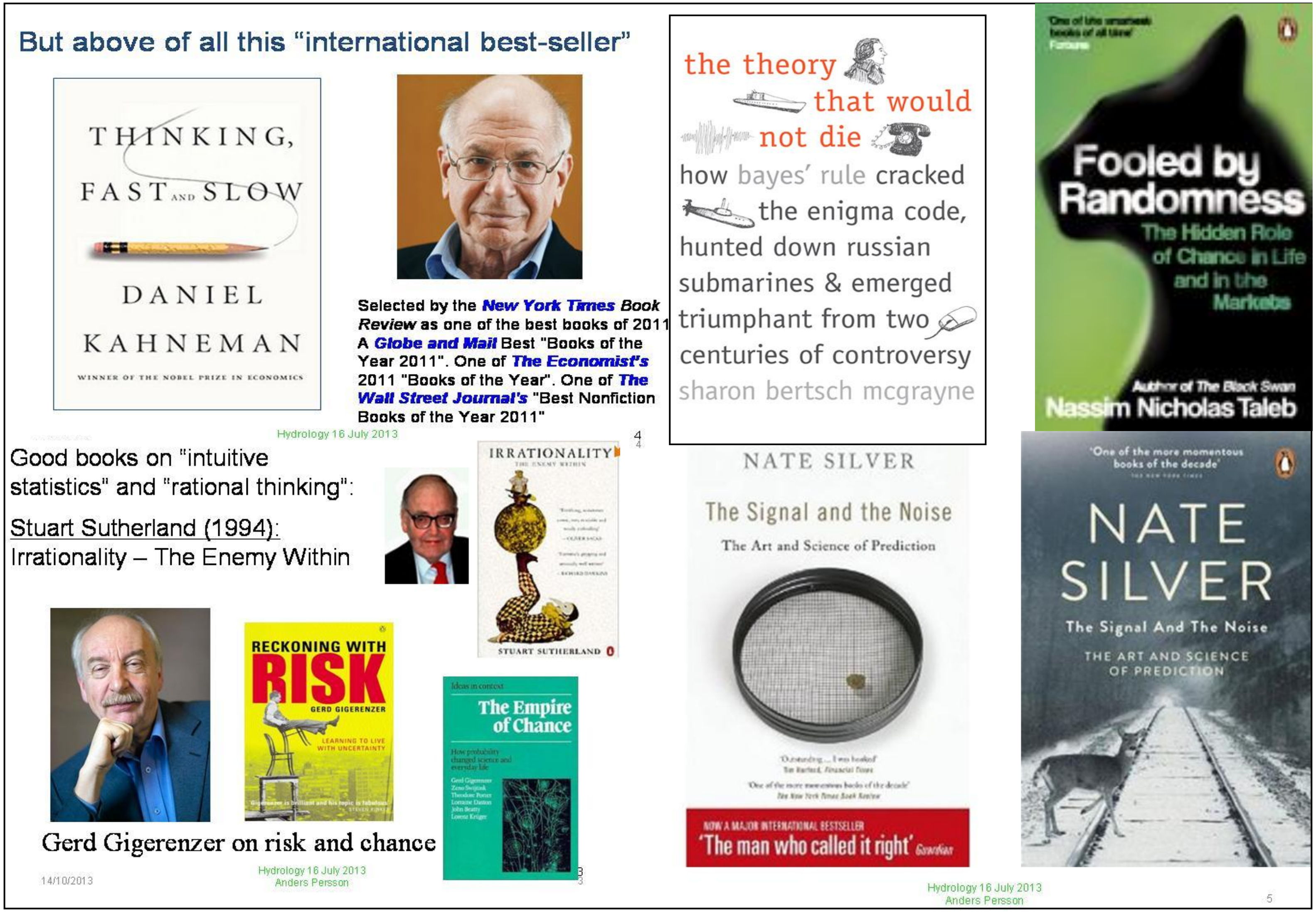
2. **Kalman filtering of computer forecast output** – *self learning equations?*

3. **A new look at the Coriolis Effect** – *it is not an optical illusion!*

4. **Rossby’s planetary waves** – *and “group velocity thonking”*

1. Decision making from probability forecasts – *turning a weakness into a strength*

A surge of books on uncertainty and intuitive statistics



Some common pitfalls

1. Over-confidence
2. The Halo Effect
3. Representativeness bias
4. Confirmation bias
5. Availability effect
6. Misleading forecast consistency
7. Probability forecasts

Some common pitfalls

1. -It will surely rain in six days time!
2. -Model A is usually best!
3. -It either rains or it is dry – not half dry!
4. -It rains - at least in Riga!
5. -Model A has nicer graphics – in colour
6. -Should we really change the forecast?
7. **-They do not tell me what to do!**

Probability forecasts really tell us what to do!

Assume we are in a region with adverse weather 30% of the time

9 days/month or 122 days/year.

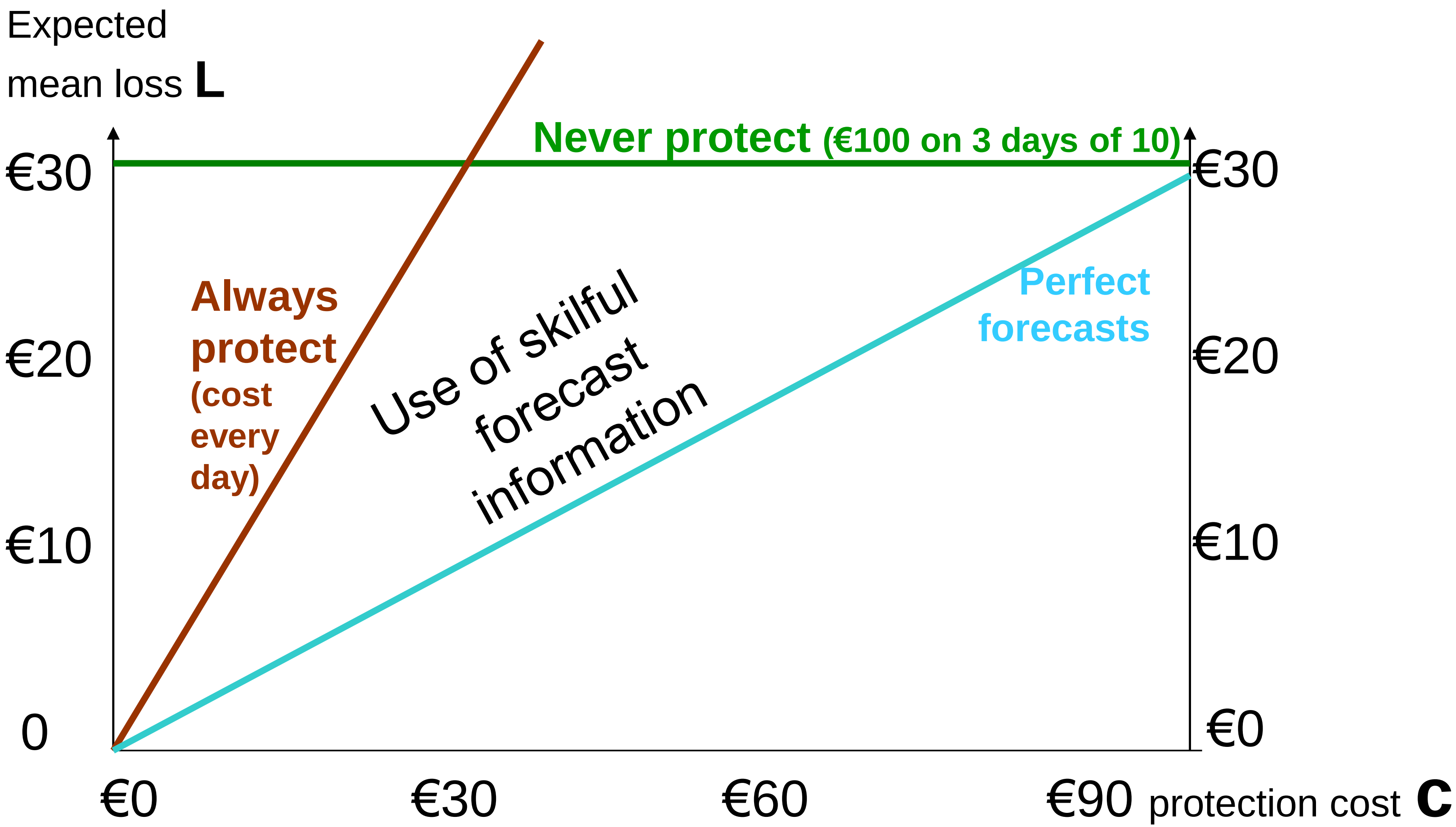
There is generally a 30% probability of rain

Assume that adverse weather will cause a loss **L = €100** per day

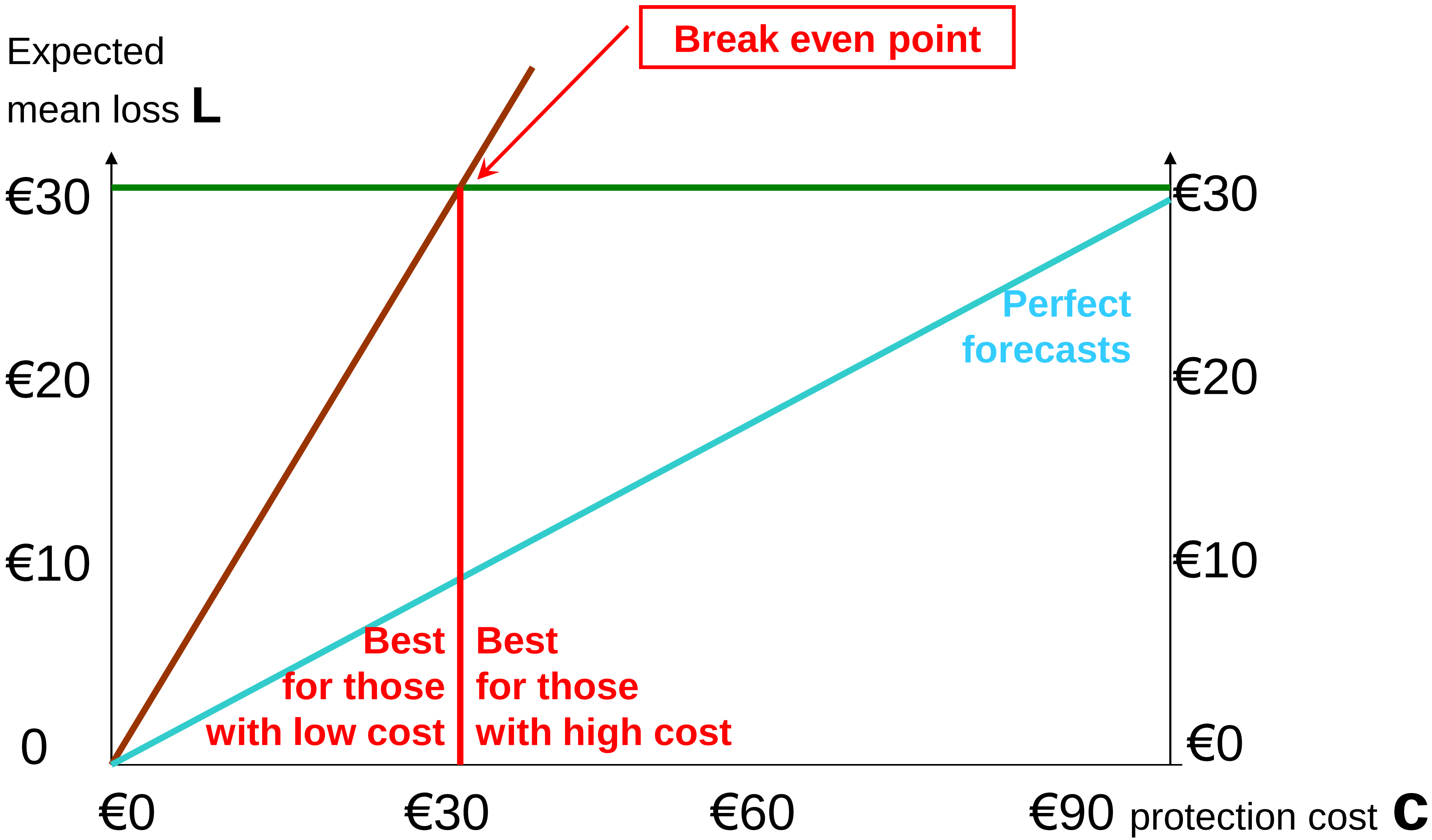
For a certain occupation the cost of protection per day may range from c = **€0** to c = **€100** **(the same as the loss)**

We can now calculate the average Expected Mean Loss per day, i.e. the average cost and loss per day if there is no forecast information

With no forecast information you can chose to a) protect every day or b) never protect



Customers with a c/L equal the climate (30%) will benefit most from the forecasts



The local weather forecasters make very good forecasts with 80% being correct.

All forecasts were well tuned:

	Obs rain	Obs dry
Fc rain	20	10
Fc dry	10	60

The number of rain forecasts (30) over 100 days matches the number of observed rain days (30)

This matrix also reflects the actions and their consequences

	Obs rain	Obs dry
Fc rain	**20**	**10**
Fc dry	**10**	**60**

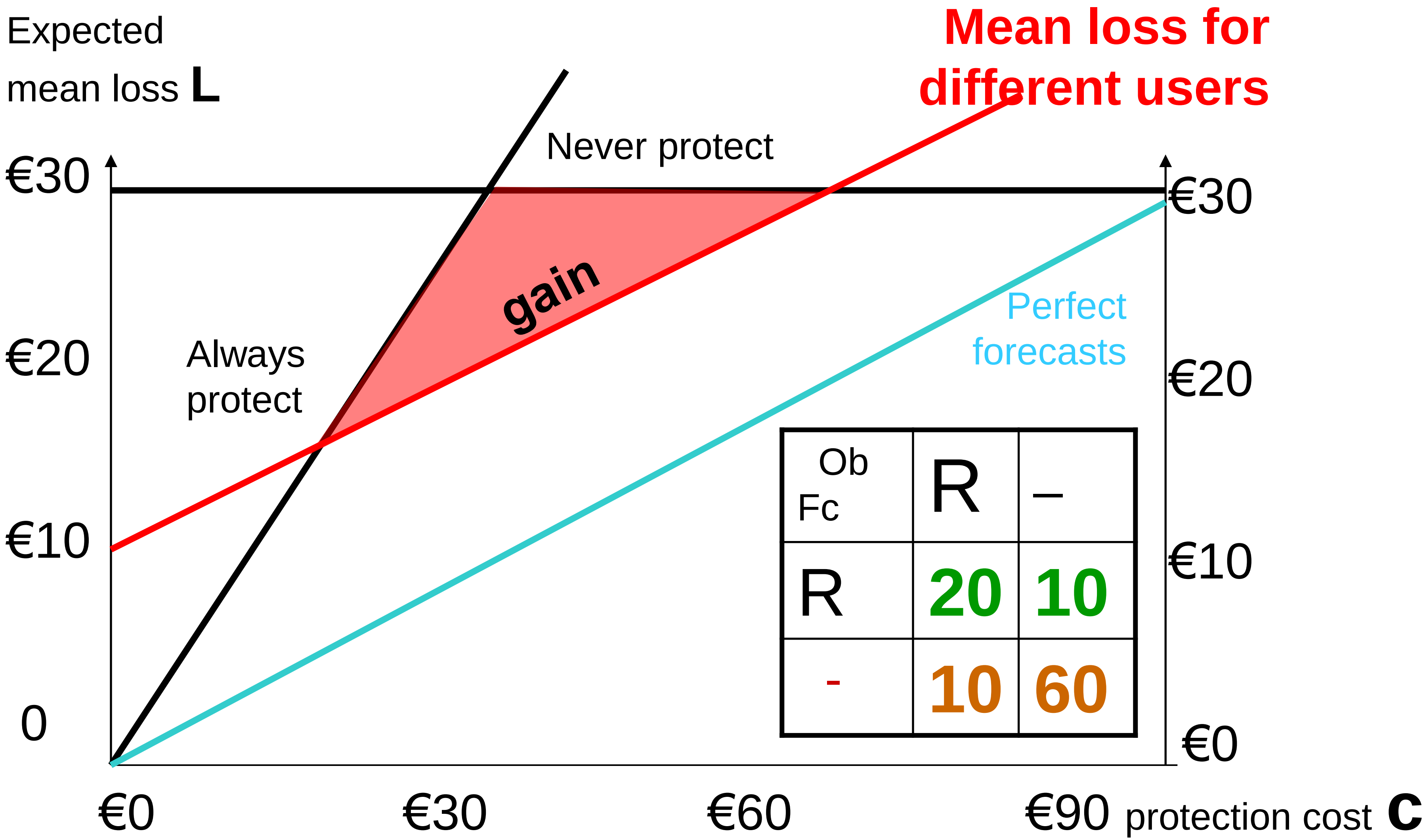
Actions were taken

No actions were taken

Losses

From this it is possible to calculate the Expected mean loss

The expected loss per day for different protection costs c



Ob / Fc	R	–
R	20	10
-	10	60

If the forecasters had chosen to become less categorical it could also have served *both* low and high cost-loss customers

	Obs rain	Obs dry
Fc rain	20	10
Fc dry	10	60

	Obs rain	Obs dry
Fc rain	10	0
???	20	20
Fc dry	0	50

50-50%

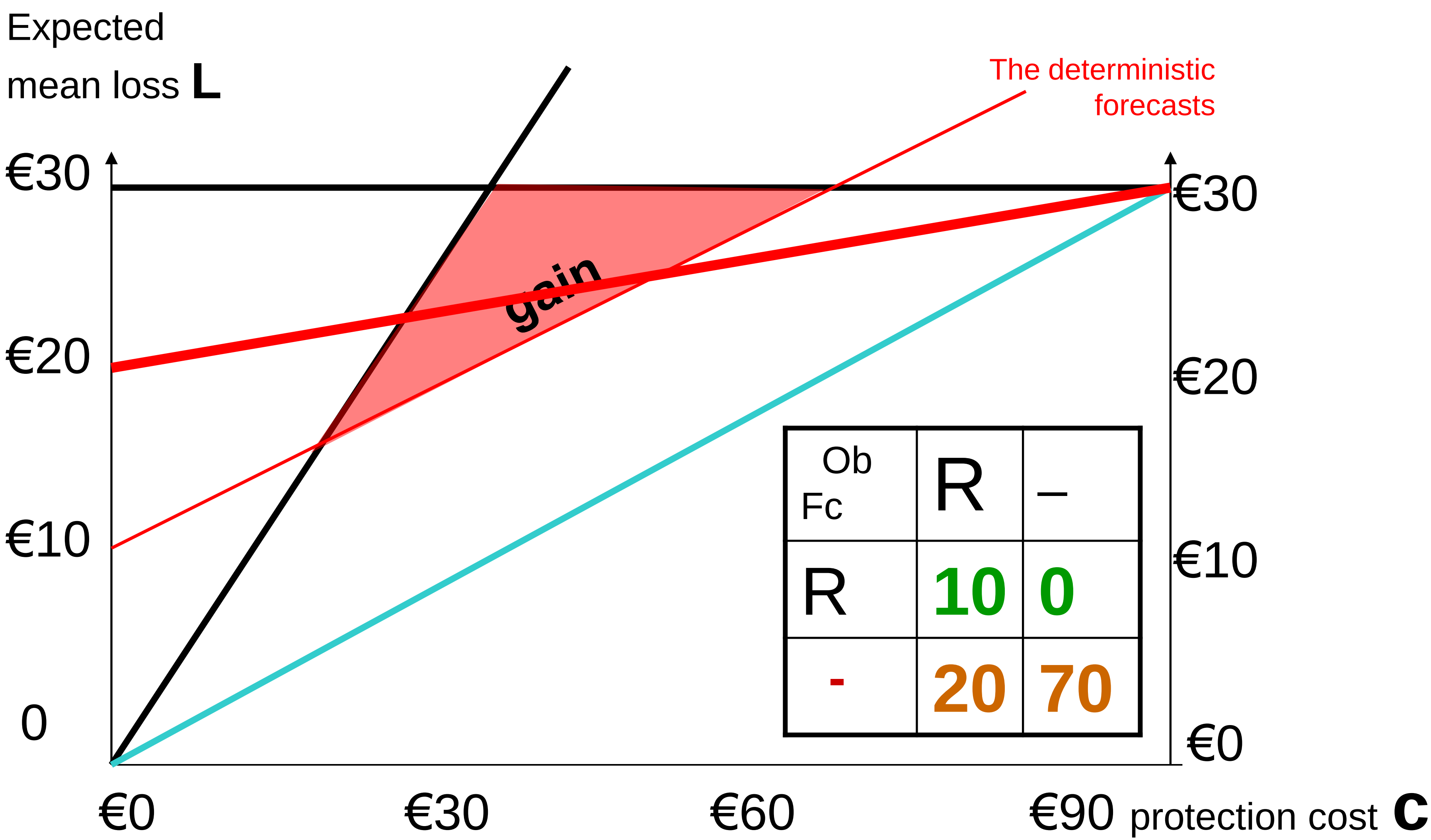
It allows those who are <u>not</u> sensitive to rain to interpret the ??? as "it might <u>not</u> rain"

	Obs rain	Obs dry
Fc rain	10	0
???	20	20
Fc dry	0	50

→

	Obs rain	Obs dry
Fc rain	10	0
Fc dry	20	70

These are the expected mean loss for those who interpreted ??? as "it might not rain"



Ob / Fc	R	–
R	10	0
-	20	70

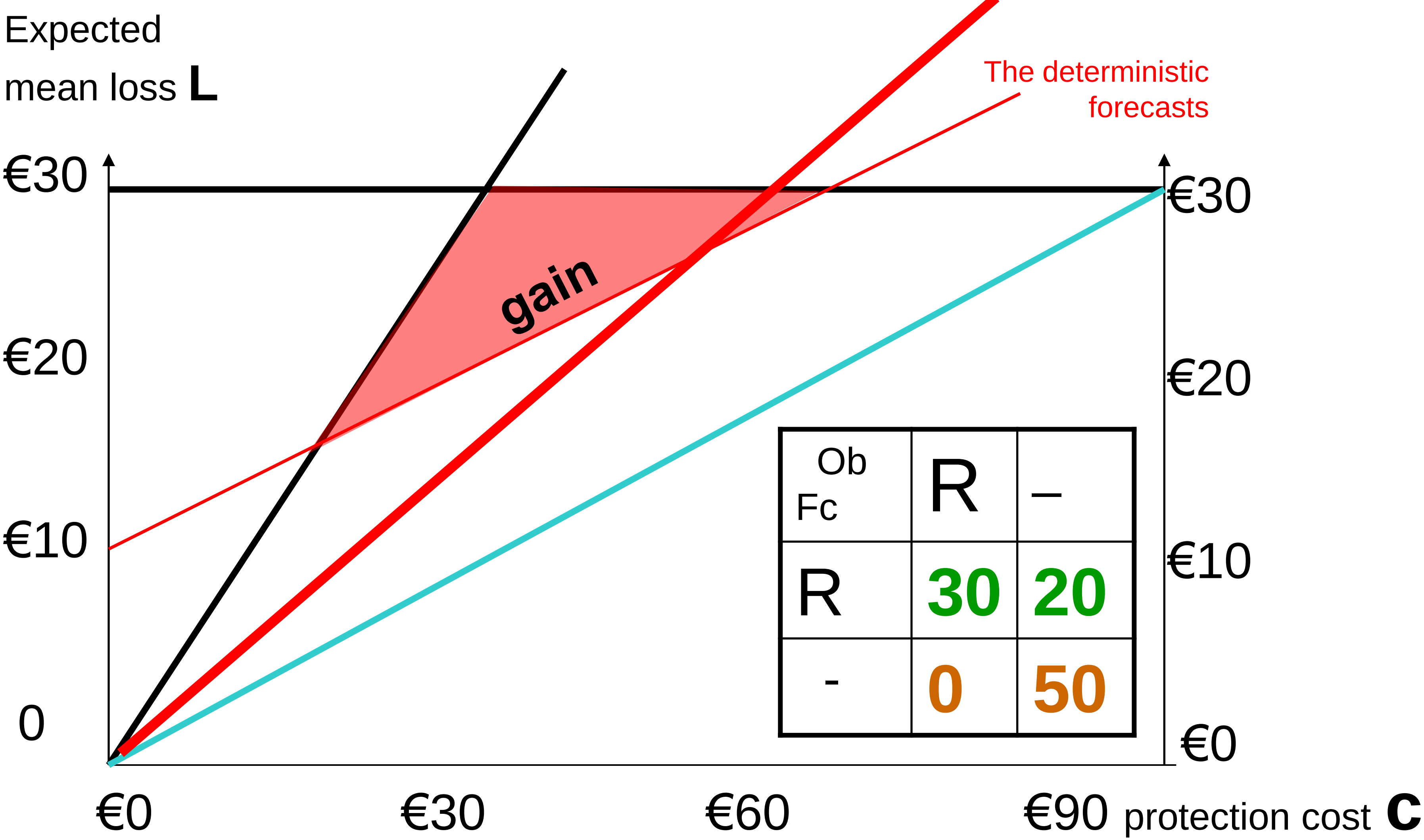
It allows those who are sensitive to rain to interpret the ??? as "it might rain"

	Obs rain	Obs dry
Fc rain	10	0
???	20	20
Fc dry	0	50

→

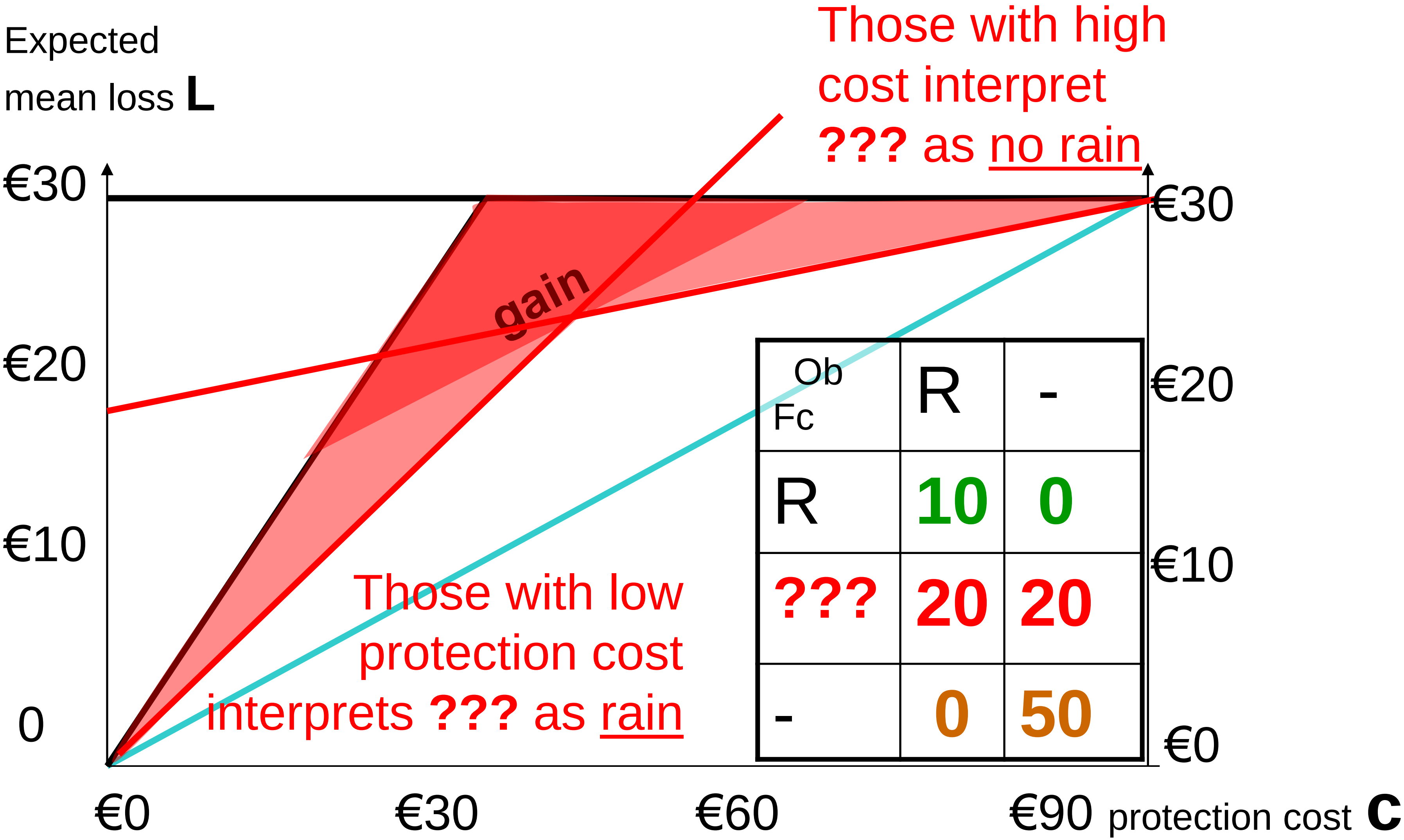
	Obs rain	Obs dry
Fc rain	30	20
Fc dry	0	50

These are the expected mean loss for those who interpreted ??? as "it *might* rain"



Ob / Fc	R	–
R	30	20
-	0	50

And them put them together . . .



Ob / Fc	R	-
R	**10**	**0**
???	**20**	**20**
-	**0**	**50**

In mid-December 2011 British meteorologists faced a difficult weather situation with great uncertainties of the track of a severe storm:

D+8 forecast 7 December

D+5 forecast 10 December

D+6 forecast 9 December

D+7 forecast 8 December

The jumpiness and uncertainty continued on D+4, D+3 and D+2

They took an active responsibility for the problem

The cyclone has changed track several times - we have revised our calculations

The BBC forecasters avoided going into detail and did not show any of their normal isobar maps

"Some terrible weather will threaten us on Thursday-Friday"

But not all of the 100 forecasts are certain

Categorical

Obs / Fc	R	–
R	20	10
-	10	60

Non-categorical

Obs / Fc	R	-
R	10	0
???	20	20
-	0	50

Probabilistic

Obs / Prob%	R	–
100	10	0
80	8	2
60	6	4
40	4	6
20	2	8
0	0	50

Can we quantify that uncertainty?

What to do with a probability **p**?

1. If you do nothing there is a chance **p** to lose **L**.

2. On average the loss will be **pL** ("risk")

3. If you take protective action it will cost **c**

4. Only if **p·L > c** is it worth while to take action

5. The "break even" point is **p = c/L**

Decision matrix for different people with c/L=100%

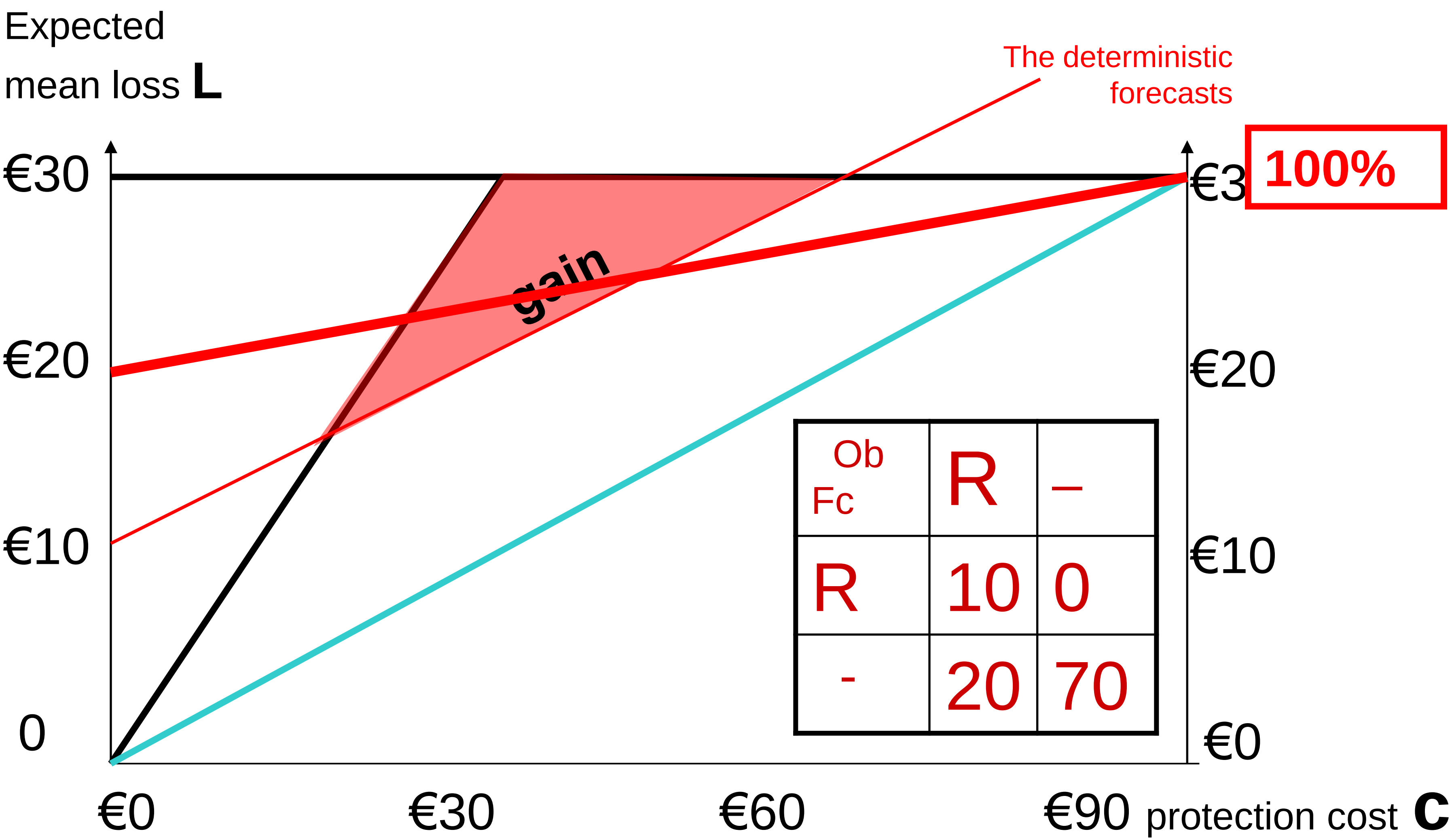
Ob Prob	R	–
100	10	0
80	8	2
60	6	4
40	4	6
20	2	8
0	0	50

Ob Fc	R	–
R	10	0
-	20	70

Decision matrix

Probability matrix

Gains for people with c/L almost 100%



Ob Fc	R	–
R	10	0
-	20	70

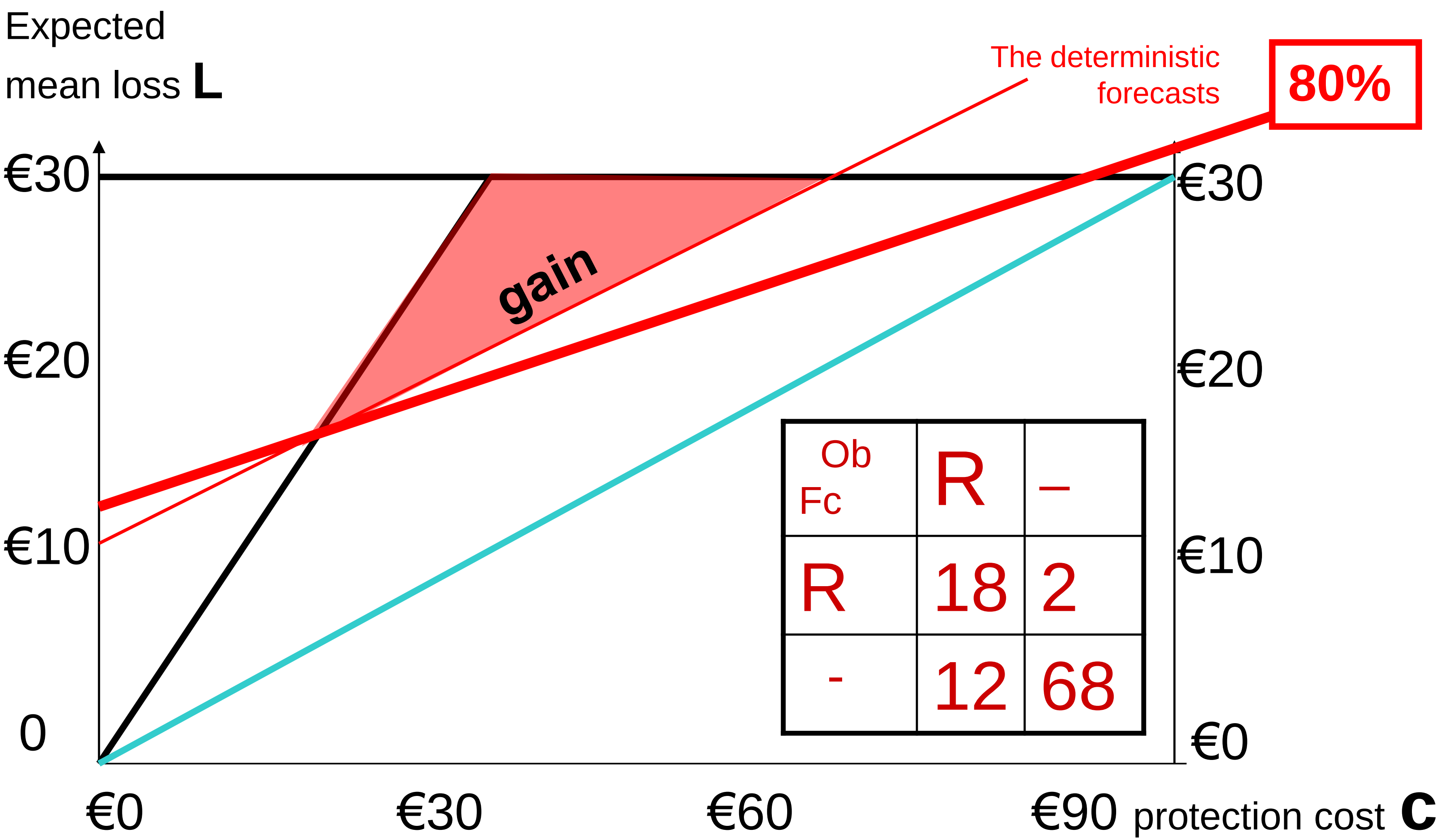
Decision matrix for people with c/L around 80%

Ob / Prob	R	–
100	10	0
80	8	2
60	6	4
40	4	6
20	2	8
0	0	50

→

Ob / Fc	R	–
R	18	2
-	12	68

Gains for people with c/L around 80%



Ob / Fc	R	–
R	18	2
-	12	68

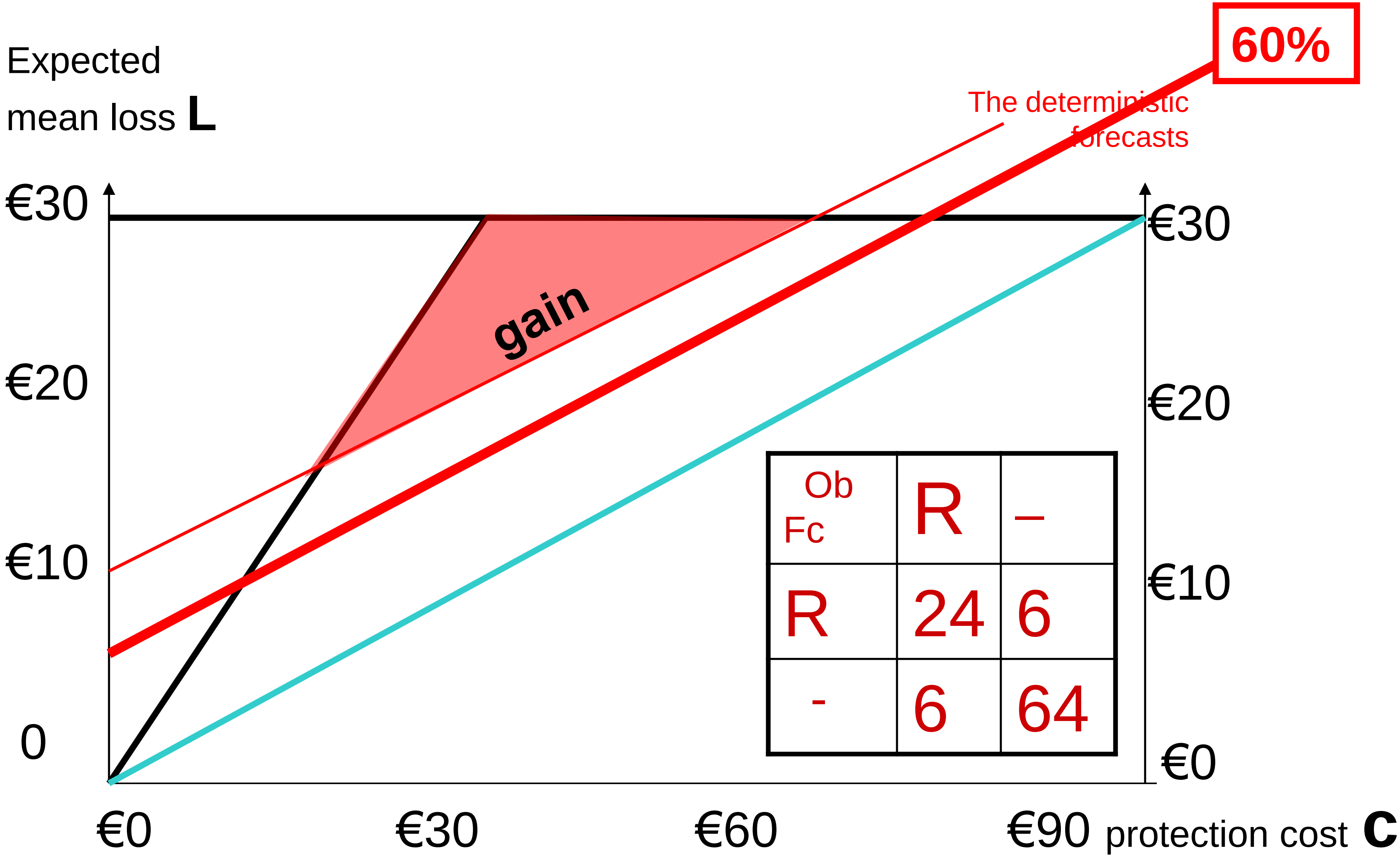
Decision matrix for people with c/L around 60%

Ob / Prob	R	–
100	10	0
80	8	2
60	6	4
40	4	6
20	2	8
0	0	50

→

Ob / Fc	R	–
R	24	6
-	6	64

Gains for different people when P = 60%



Fc \ Ob	R	–
R	24	6
-	6	64

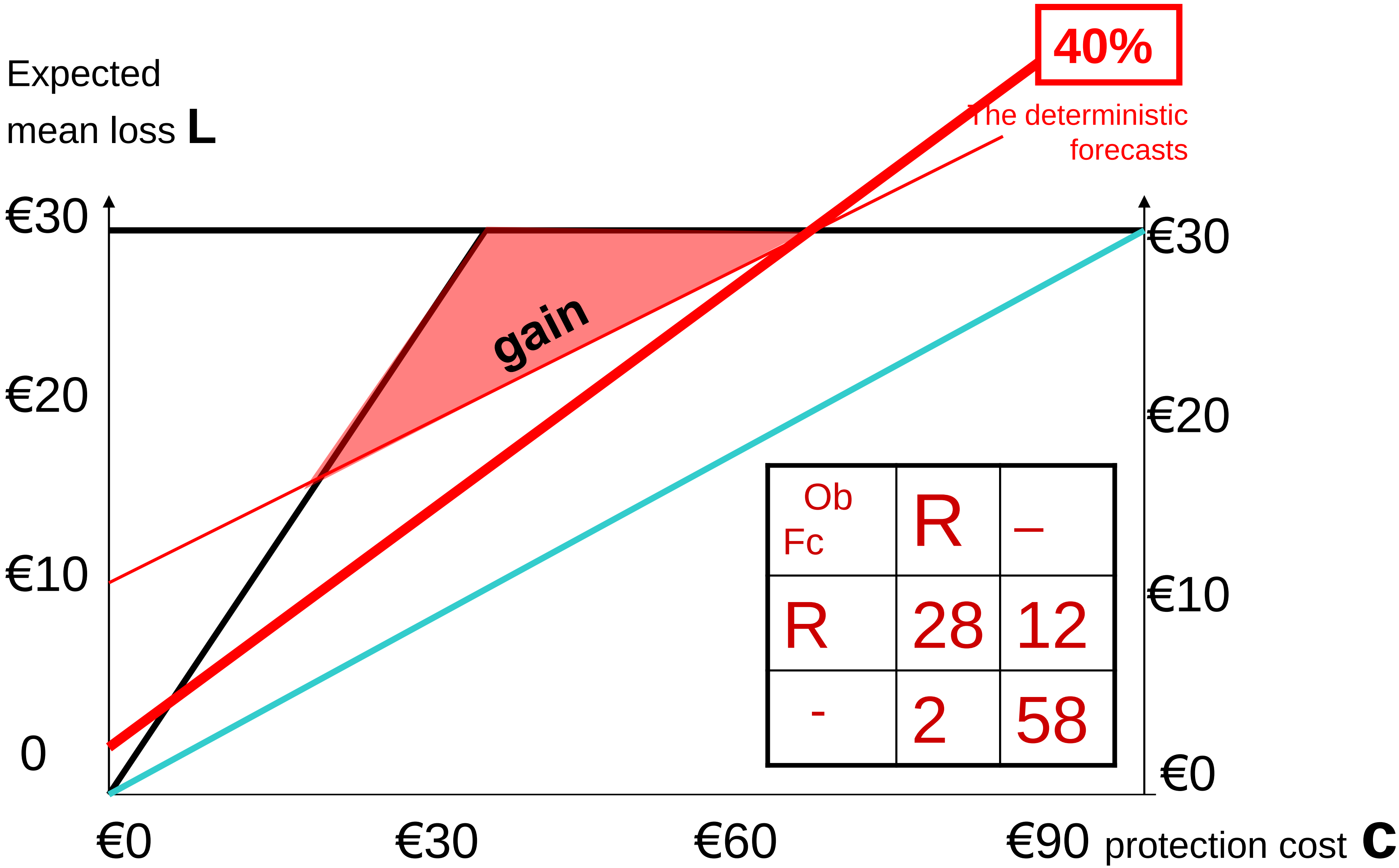
Decision matrix for people with c/L around 40%

Ob Prob	R	–
100	10	0
80	8	2
60	6	4
40	4	6
20	2	8
0	0	50

→

Ob Fc	R	–
R	28	12
-	2	58

Gains for people with c/L around 40%



Fc \ Ob	R	–
R	28	12
-	2	58

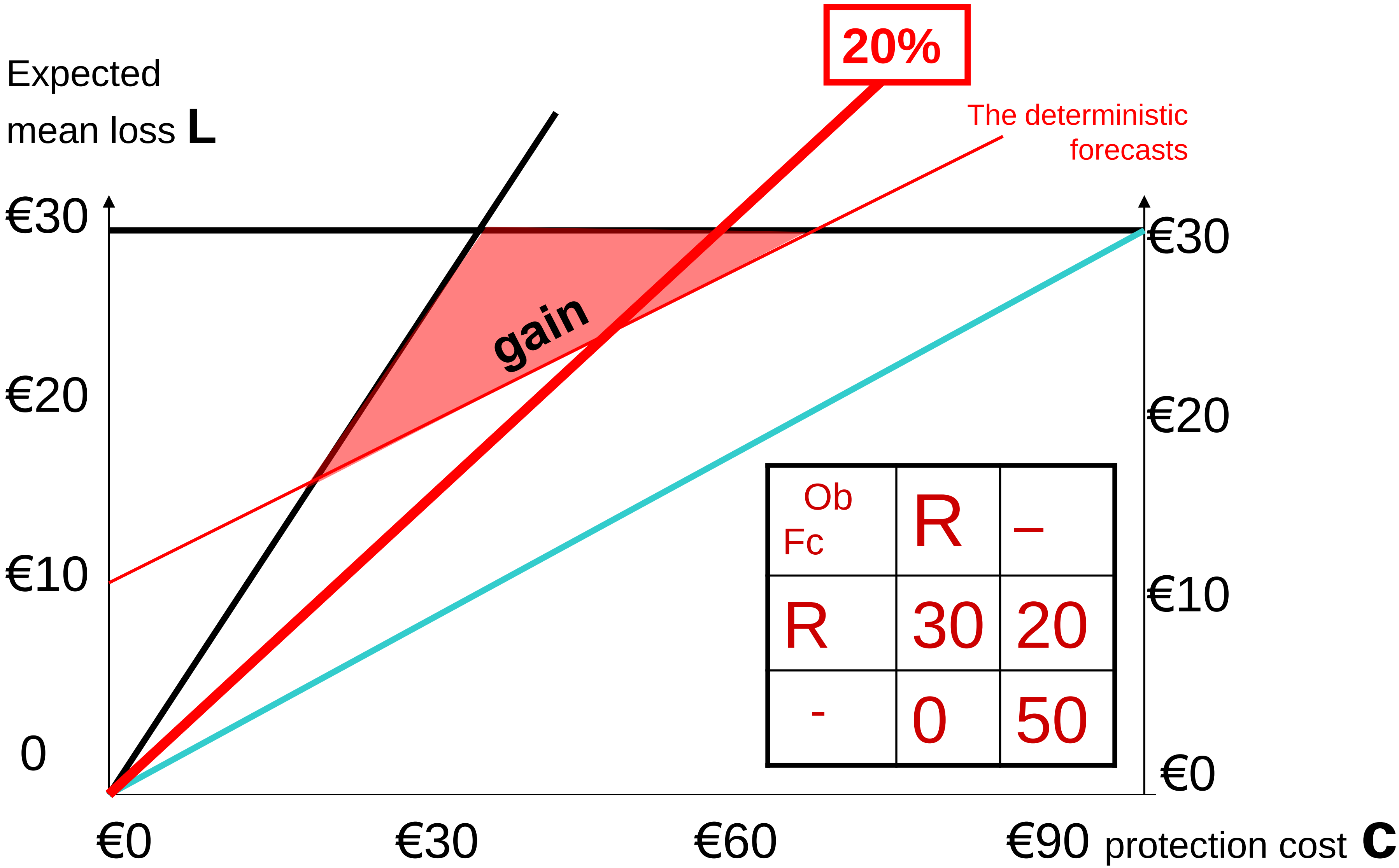
Decision matrix for people with c/L around 20%

Ob / Prob	R	–
100	10	0
80	8	2
60	6	4
40	4	6
20	2	8
0	0	50

→

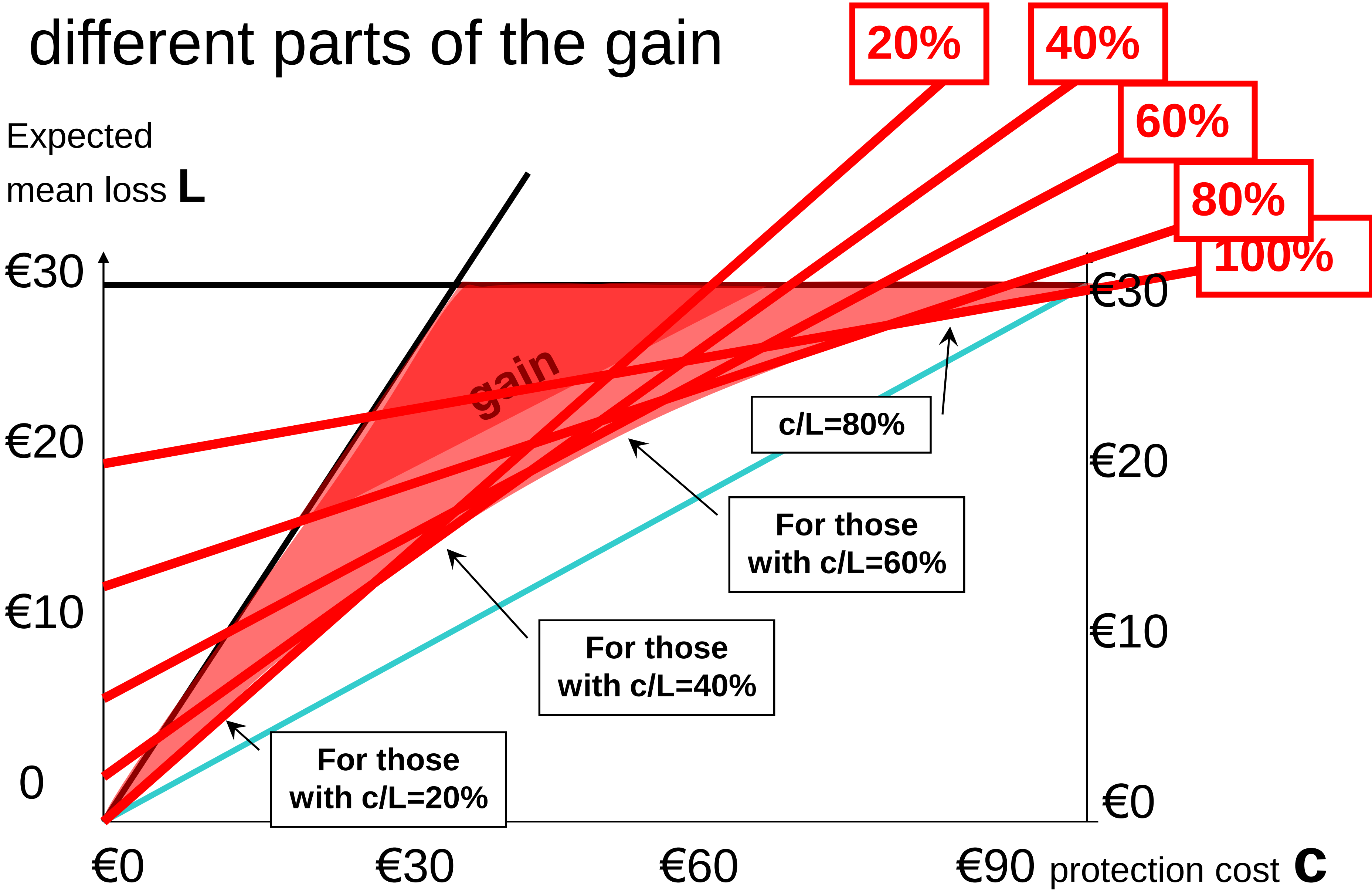
Ob / Fc	R	–
R	30	20
-	0	50

Gains for people with c/L around 20%

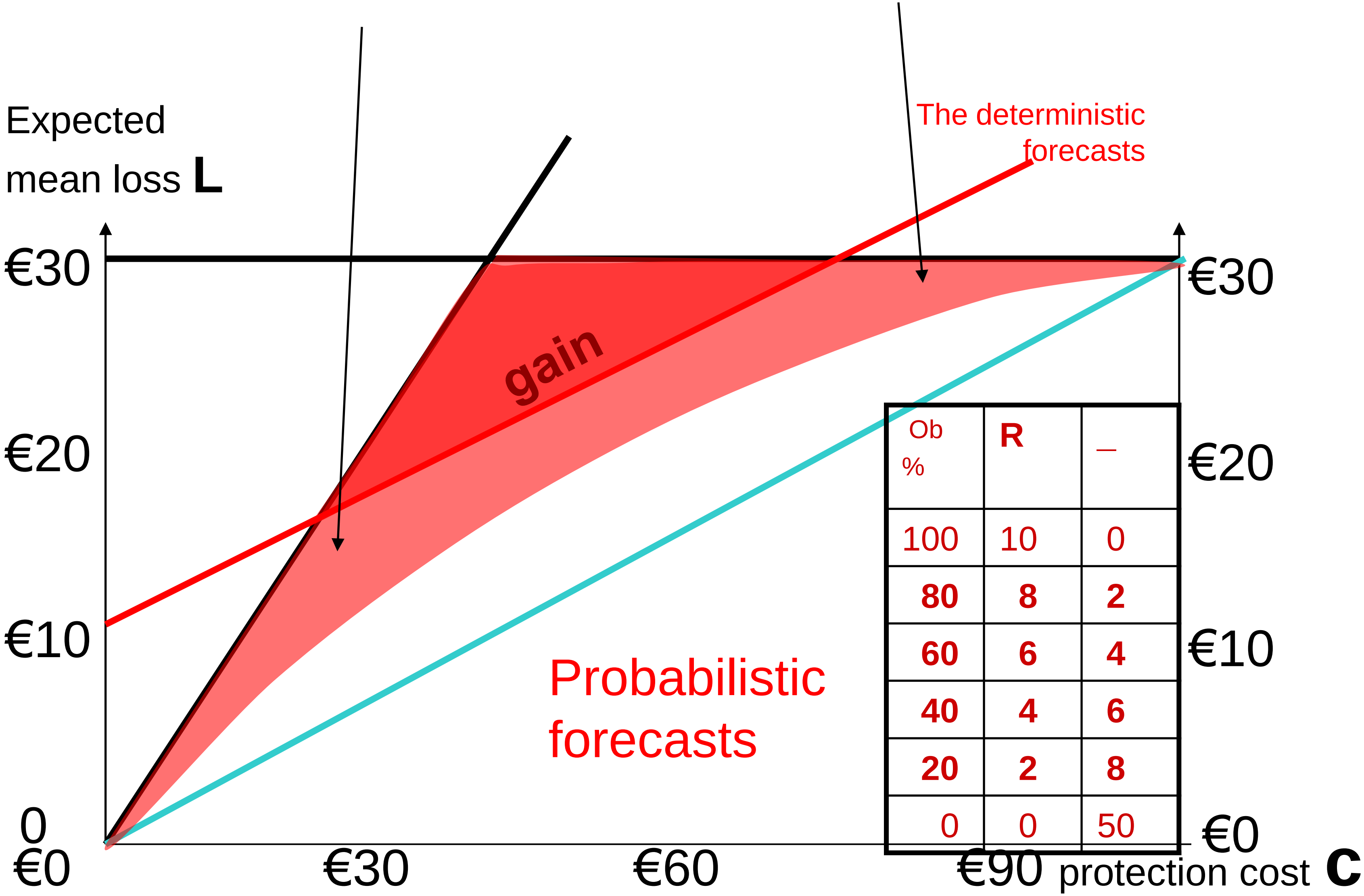


Ob / Fc	R	–
R	30	20
-	0	50

Different users benefit from different parts of the gain



Probabilities yield gains for <u>all</u> possible protection costs



Ob %	R	—
100	10	0
80	**8**	**2**
60	**6**	**4**
40	**4**	**6**
20	**2**	**8**
0	0	50

END