Portfolio Credit Risk

University of Chicago Masters in Financial Mathematics 36702

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Lecture 4

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Conditional LGD risk

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Lecture 3 greatest hits

For any loan, Loss = D * LGD

In any set of conditions, cLoss = cPD * cLGD

For any loan, EL = E [Loss]

$$
\begin{aligned}
EL &= E[\,Loss\,] \\
&= E[\,D * LGD\,] \\
&= E[\,D\,] * E[\,LGD\,] \quad \text{(this is the mystery step)} \\
&= PD * ELGD
\end{aligned}
$$

- **Independence because: LGD means "Loss Given Default."**
  - **LGD is the fraction that is lost if there is a default.**
  - **If there is a default, what is the fraction that is lost?**
  - **No mystery! LGD can depend on many things, but it cannot depend on the default of the loan because LGD already assumes the default of the loan.**

Any thoughts before we start?

Questions or comments?

This session is probably the most difficult of the 5.

Pep talk

You might get a job where you model conditional LGD.

- “Stress tests" are required of big banks.
- “Current expected credit loss" (CECL) is required of all banks.
- Credit default swaps, and OTC derivatives in general, are also subject changing values of LGD in changing conditions.

You might get involved in risks where data is sparce.

- With sparce data, a simpler model is less likely to be overfit.
  - Tonight, you’ll see a model that is simpler than linear regression.
  - It is based on something obvious.
  - Things get messy only when the model is subjected to statistical test.

Week 4 topics

Four ways to model conditional LGD

LGD functions

The Frye-Jacobs LGD function

Testing the Frye-Jacobs LGD function

Four ways to model cLGD

Four ways to model cLGD

1. **Ignore it.**
2. **Pretend to not ignore it, then ignore it.**
3. **Model cLGD separately from cPD.**
   - **The product, cLoss, has nonsensical behaviors that have given banks nonsensical incentives.**
4. **Start fresh modeling cLGD.**
   - **Every loan has an LGD function.**
   - **Frye and Jacobs make a particular choice.**
   - **The Frye-Jacobs LGD function is *<u>testable</u>*,**
     - **and it has survived testing so far.**

1. Ignore, ignore, ignore

Of the approaches to systematic LGD risk, ignoring it has the longest history and greatest popularity.

This approach makes the simulation model easy:

- **Simulate the defaults as usual.**
- **In each run, Loss = DR * ELGD; ELGD is a fixed number.**
- **Done.**

CreditMetrics© makes this slightly more sophisticated:

- **In it, LGD is random, but the distribution of LGD *does not depend* on conditions in the simulation run.**
  - **The only LGD risk comes from the randomness of a small portfolio.**

2. Pretend to not ignore

To pretend to not ignore systematic LGD risk, do this:

- **Test H_0: LGD does not respond to economic variables.**
- **Assemble data of such poor quality that H_0 is not rejected.**
- **Conclude that *there* *is* *no* systematic LGD risk.**

Note the sequence of steps:

- **H_0 is implausible.**
  - **LGD is an *economic* variable. Why should it be independent of others?**
- **Be sure to use a short, poor-quality data set.**
- **Then, conclude that the implausible hypothesis is *true*.**

As you can imagine, the people who do this have PhDs.

Few believe it anymore

- When I wrote Collateral Damage (2000), there was one carefully observed downturn, 1990-91.
  - I found that LGD went up significantly in 1990-91.
    - Skeptics still believed that LGD is independent of other variables.
- In the tech recession (2001), LGD went up again.
  - Basel II acknowledged that LGD goes up and down.
    - LGD in Basel II became the confusing mess that you saw earlier.
- In the 2008 crisis, LGD went up again.
  - You already saw the LGD chart with the three spikes.
- It is now agreed that LGD goes up in times of stress.
    - I hoped that Covid 19 would produce a good downturn, but no.

3. Model LGD naively

The naïve approach handles LGD and default separately.

- The bank's ***loss*** model is the product of the default rate model and the LGD model.
  - The distribution that results contains all the parameters from the default model and all of those from the cLGD model. Complicated! And, worse…

The result allows arbitrage of the capital requirement.

- (1): Loosen the definition of default.
- (2): The newly-recognized defaults have zero loss.
- (3): This affects both the default model and the LGD model.
- (4): In the Basel formula, required capital goes down.
- Banks busied themselves loosening the definition of default.
  - This actually happened…

Basel implementation

A historical loan was a "default" if the bank lost money.

- **Interns identified defaults using paper documents from long, long ago.**

But then the banks did the Basel calculation.

- **What if "default" included when payment was 90 days late?**
  - **The interns would found more, not less, defaults in the historical data.**
  - **The newly discovered defaults caused zero loss to the bank.**
  - **Therefore, average historical LGD would be less.**
  - **The reduction in LGD had a bigger effect on required capital than the increase in the historical default rate.**

The change of definition *reduced* required capital…

$$K = \left[LGD \times N\left(\frac{N^{-1}(PD) + \sqrt{R} \times N^{-1}(0.999)}{\sqrt{1-R}} \right) - (LGD \times PD) \right] \times \left(\frac{1 + (M - 2.5) \times b}{1 - 1.5 \times b} \right)$$

		Definition 1			Definition 2	
Loan		Default	Loss		Default	Loss
1		0	0		0	0
2		0	0		0	0
3		0	0		0	0
4		0	0		1	0
5		1	0.5		1	0.5

Definition 1:

EL = .5/5 = 0.1

PD = 1/5 = 0.2

ELGD = .1/.2 = 0.5

Basel formula: $.5 * \Phi\left[\frac{\Phi^{-1}[.2] + \sqrt{.1}\,\Phi^{-1}[.999]}{\sqrt{1-.1}}\right] - .5 * .2$

= 0.28

Definition 2:

EL = .5/5 = 0.1

PD = 2/5 = 0.4

ELGD = .1/.4 = 0.25

$.25 * \Phi\left[\frac{\Phi^{-1}[.4] + \sqrt{.1}\,\Phi^{-1}[.999]}{\sqrt{1-.1}}\right] - .25 * .4$

= 0.19

4. Start fresh modeling LGD

The definition of default should *not* affect loss.

- **If there is a change in the definition of default, then the value of LGD should change to offset it: cLGD = cLoss / cPD.**

We have the Vasicek PDF for cPD.

If there is a nice expression for cLoss, we might be able to back out cLGD.

Questions? Comments?

LGD functions

What would an LGD function do?

I'll show that every loan *has* an LGD function

An LGD function has three inputs

PD: The probability of default in the next 12 months

- **PD depends on the firm, its financial condition, etc.**

ELGD: The expected LGD of the loan

- **ELGD depends on seniority, security, guarantees, etc.**

cPD: The *conditional* probability of default.

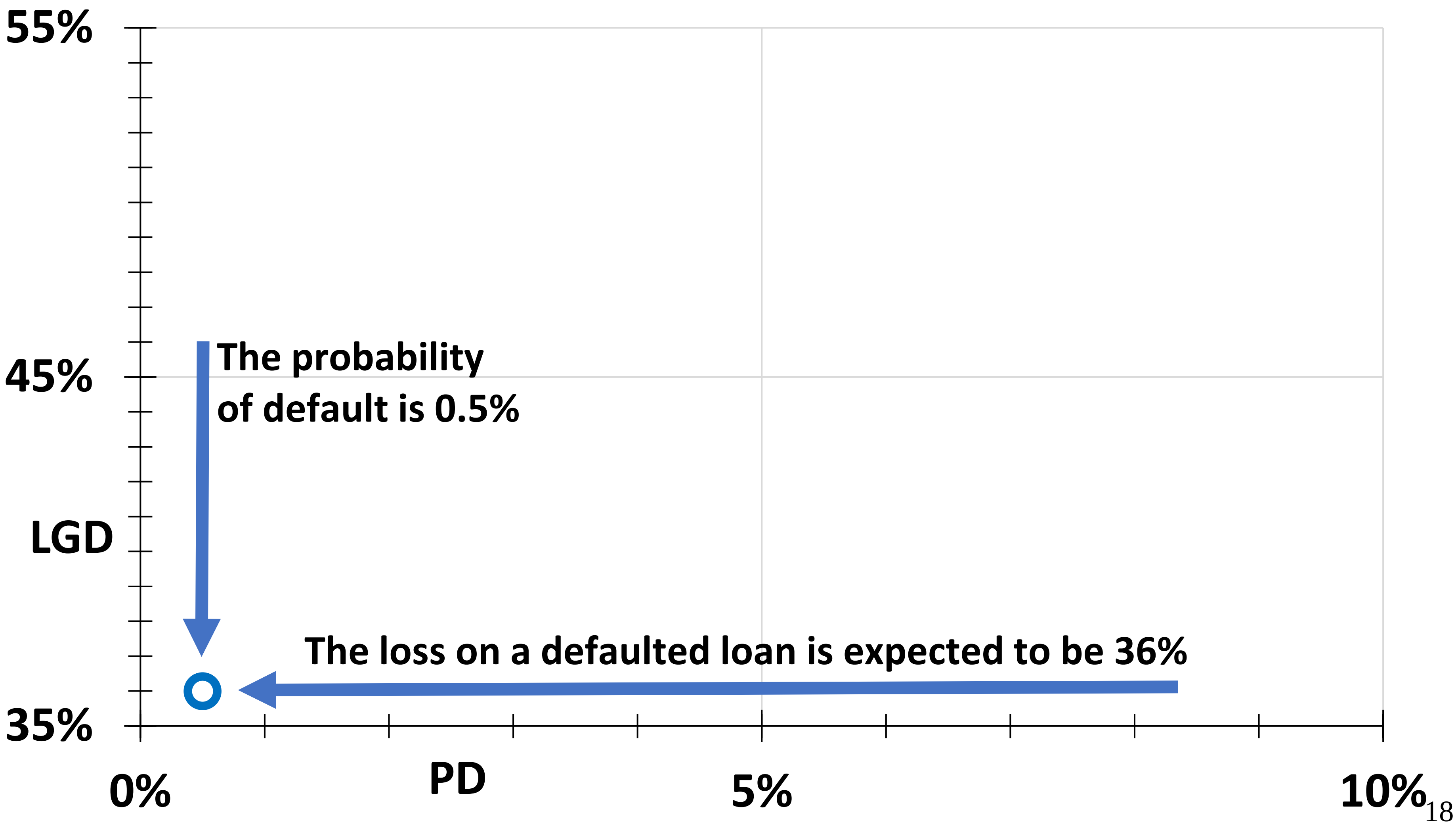
- **The conditions are those present in some scenario.**
  - **In our single-factor models, conditions are determined by Z.**
  - **In a FR stress test, conditions are defined by hypothetical values of several macroeconomic variables.**
    - **Then, cPD would be the "stress default rate."**

Along with these three, there could be others.

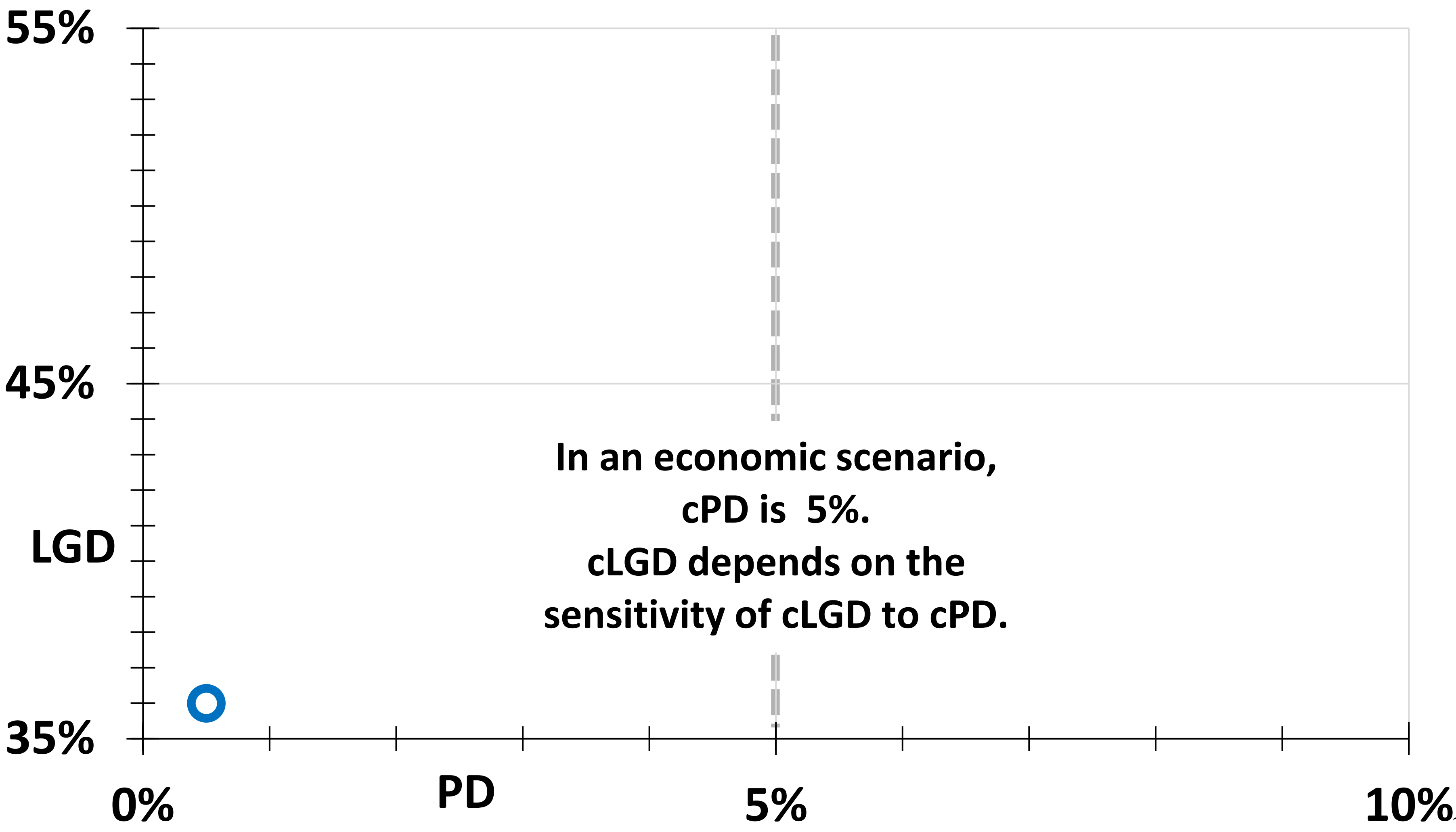
The output is *conditional* LGD, cLGD.

- **cLGD is the LGD to be expected in the conditions that produce cPD; sometimes referred to as "stress LGD."**

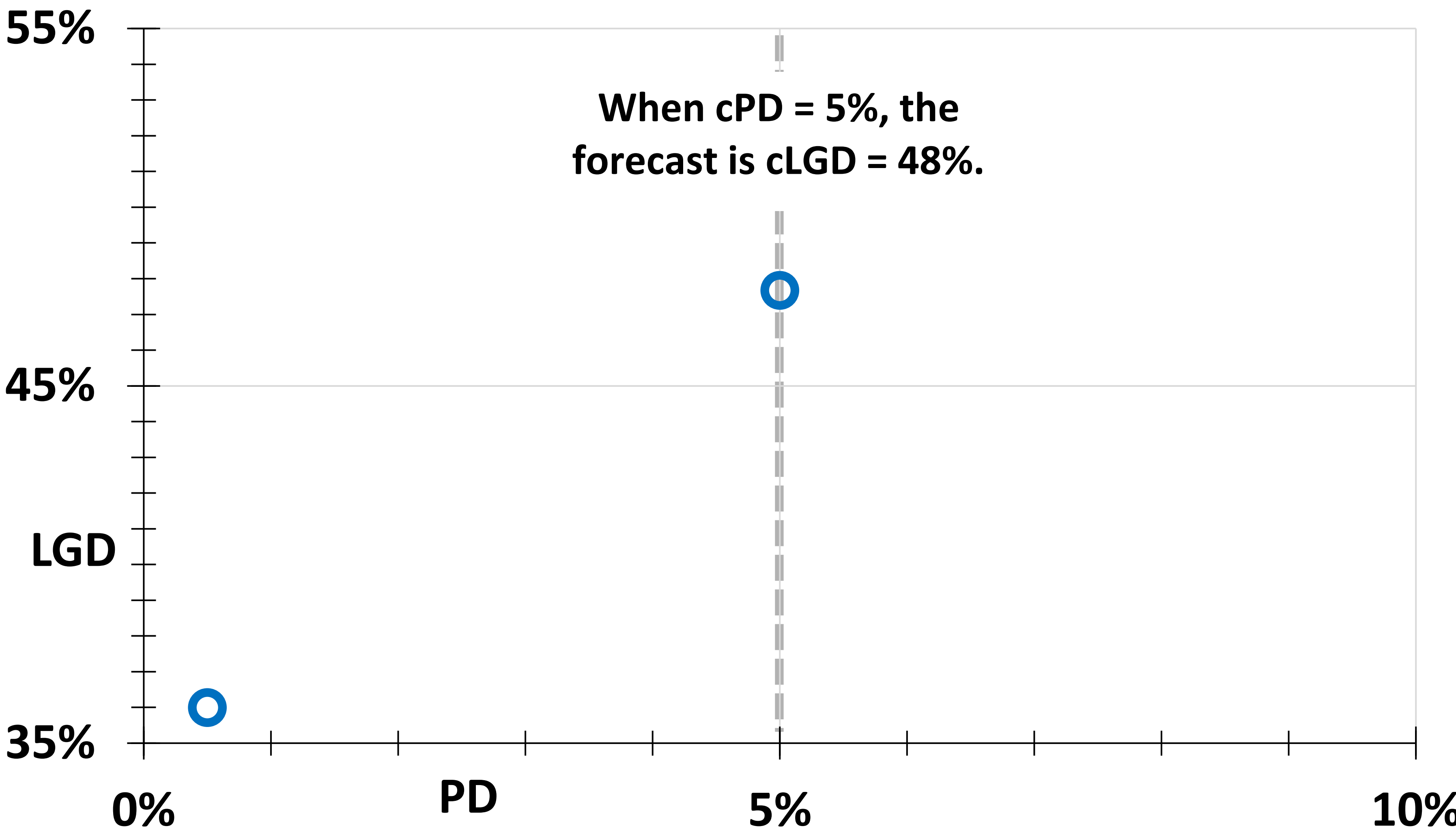
The first two inputs



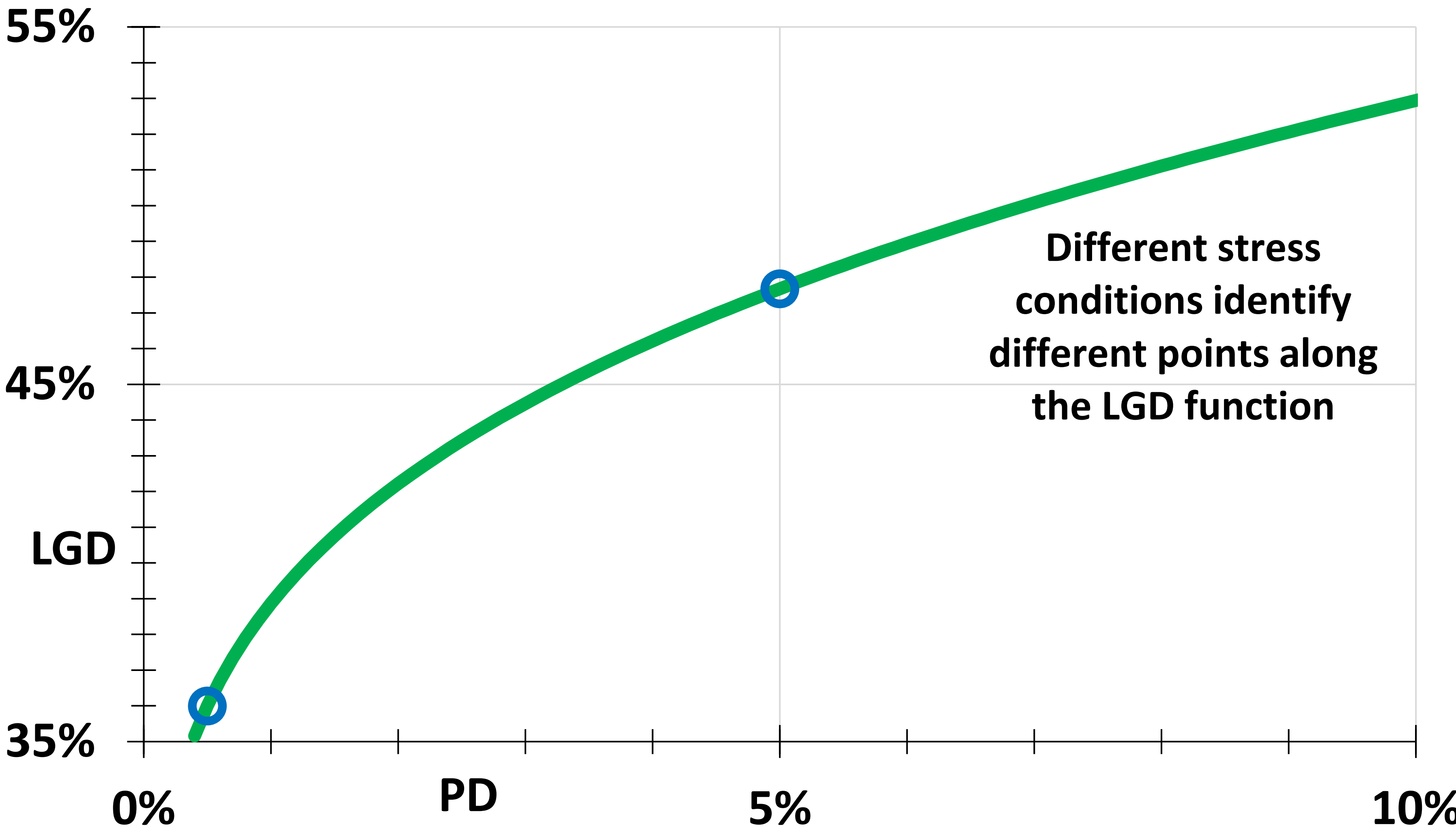
The third input



The value of the LGD function



An LGD function



Questions? Discussion?

An LGD function forecasts cLGD for a loan,

given cPD and the loan-specific inputs PD, ELGD.

The simplest LGD function would have no other inputs or parameters.

Every loan has an LGD function

The key assumption

Of two sets of economic conditions, the one with greater conditional default has greater conditional loss.

If this assumption is violated, the following can occur:

	cPD	cLoss
Scenario A	10%	4%
Scenario B	<10%	> 4%

It is hard to imagine conditions that would be expected to bring about less default and more loss.

Frye-Jacobs assumes cPD and cLoss are *comonotonic*.

Comonotonicity

Comonotonicity generalizes perfect correlation.

- **If X is at its q^{th} quantile, then Y is at its q^{th} quantile.**
  - **With perfect correlation, X and Y are on a straight line.**
  - **With comonotonicity, the line can be curved.**
- **Comonotonic variables go up and down together.**

An LGD function

Because cPD and cLoss are comonotonic, the value of cLGD consistent with cPD is this:

- **Begin with a value of cPD.**
- **Find its quantile within the Vasicek distribution of cPD.**
- **Find the value of cLoss at the *same* quantile.**
  - **Same quantile because the variables are comonotonic.**
- **cLGD = cLoss / cPD.**

Therefore, an LGD function has this form:

$$\boldsymbol{cLGD\,[\,cPD\,] = CDF^{-1}_{cLoss}\,[\,CDF_{cPD}\,[\,cPD\,]\,]\;/\;cPD}$$

The same logic applies to every loan.

Therefore, every loan has an LGD function.

$$cLGD[cPD] = CDF_{cLoss}^{-1}\Big[CDF_{cPD}[cPD]\Big]/cPD$$

An LGD function takes a single random argument, cPD.

- **Non-random variables can affect cLGD.**
  - **Example: It matters whether the loan is secured or not.**
  - **Non-random variables are parameters in the distributions of cPD and cLoss.**
- **Random variables can affect cLGD *only* through effect on cPD.**
  - **Interactions between inputs could disrupt the assumed comonotonicity.**
  - **No need for an ad-hoc search for correlations than can be spurious.**

Every loan has an LGD function.

Questions? Comments?

The Frye-Jacobs LGD function

Derivation

Alternative hypotheses

Finite portfolios

The tests

The Frye-Jacobs LGD function

Every loan has an LGD function, and its form depends entirely on two CDFs.

F-J assume that cPD has a Vasicek distribution.

- This assumption led to explicit formulas.

F-J assume that cLoss also has a Vasicek distribution, and that its value of ρ is ***identical***.

- This assumption led to a simpler result.
- Besides ρ, the other parameter of a Vasicek distribution is its expectation. This is EL.

Frye-Jacobs derivation

cPD ~ Vasicek [PD, ρ]; $F_{cPD}[cPD] = \Phi\left[\frac{\sqrt{1-\rho}\,\Phi^{-1}[cPD] - \Phi^{-1}[PD]}{\sqrt{\rho}}\right]$,

cLoss ~ Vasicek [EL, ρ]; $F_{cLoss}^{-1}[q] = \Phi\left[\frac{\Phi^{-1}[EL] + \sqrt{\rho}\,\Phi^{-1}[q]}{\sqrt{1-\rho}}\right]$

$$cLGD\,[\,cPD\,] = F_{cLoss}^{-1}\,[\,F_{cPD}\,[\,cPD\,]\,]\;/\;cPD$$

$$= \Phi\left[\frac{\Phi^{-1}[EL] + \sqrt{\rho}\;\Phi^{-1}\left[\Phi\left[\frac{\sqrt{1-\rho}\;\Phi^{-1}[cPD] - \Phi^{-1}\,[PD]}{\sqrt{\rho}}\right]\right]}{\sqrt{1-\rho}}\right]\;/\;cPD$$

$$\underbrace{= \Phi\left[\Phi^{-1}[cPD] - k\right]/cPD}_{\textbf{LGD function}};\quad \underbrace{k = \left(\Phi^{-1}[PD] - \Phi^{-1}[EL]\right)\,/\,\sqrt{1-\rho}}_{\textbf{Definition of } k}$$

LGD function ; Definition of k

LGD function properties

$$\mathbf{cLGD} = \Phi\left[\Phi^{-1}[cPD] - k\right]/cPD$$

This function is monotonic increasing in cPD.

- **I found this difficult to prove. Give it a shot and let me know!**
- **If the ρ*'s* are different, then the LGD function is non-monotonic or has other unwanted characteristics.**

k summarizes the effects of parameters PD, EL, and ρ:

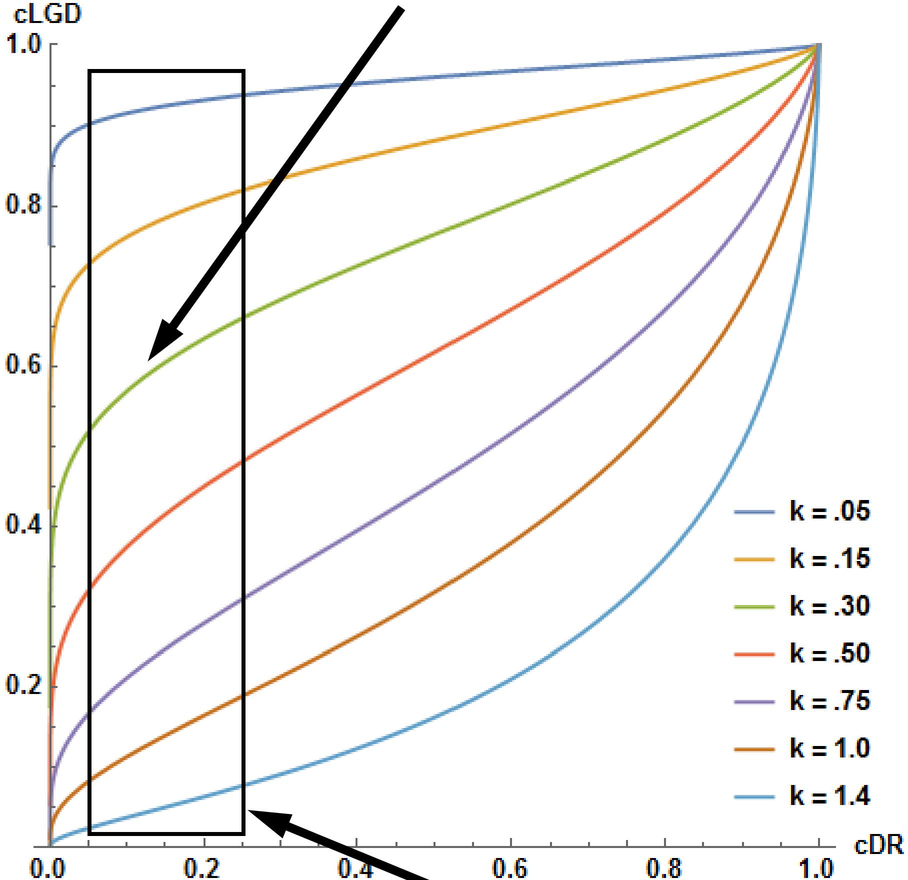
$$k = \frac{\Phi^{-1}[PD] - \Phi^{-1}[EL]}{\sqrt{1-\rho}}$$

- **It is worth noting that ρ has *little effect*.**
  - **E.g., if $\rho = 0.19$, then the denominator is 0.90.**

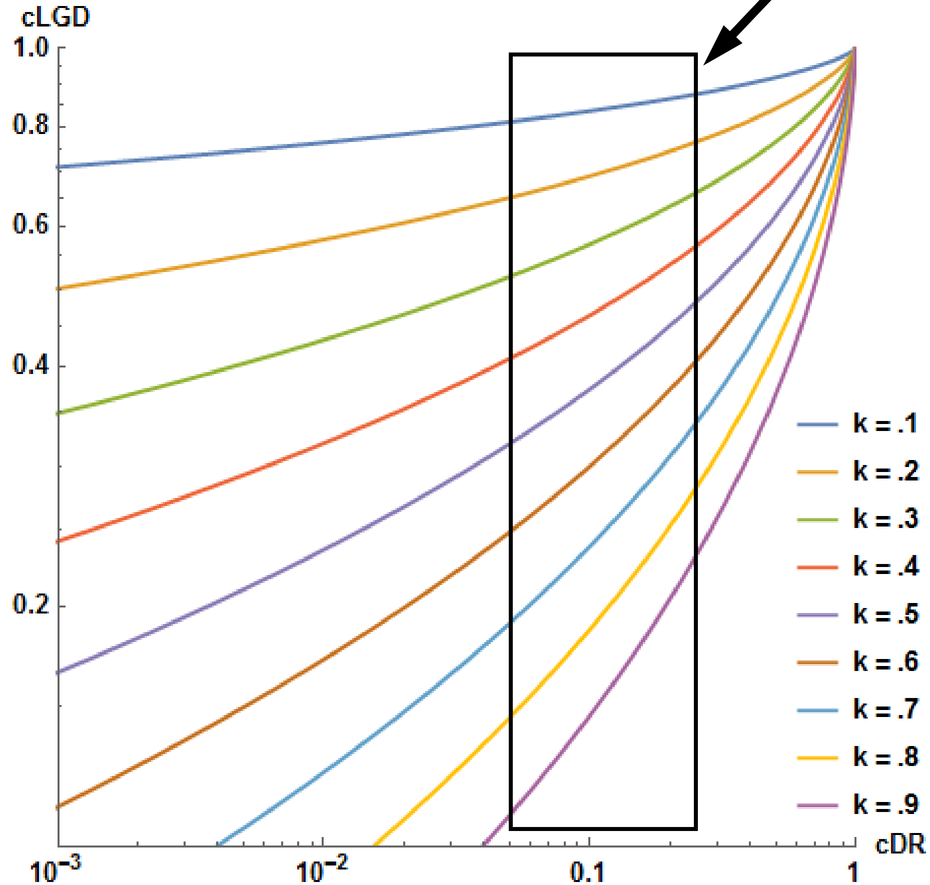
The properties are broadly consistent with observation…

1: Bounded on unit square and monotonic

2: Risk is moderate at low cDR



4: Elasticity is greater for greater k



3. Slope is *similar* for all loans on 5% < cPD < 25%.

Questions? Comments?

Toward testing the LGD function

Most of the Frye-Jacobs paper is devoted to an attempt to reject the Frye-Jacobs LGD function in a hypothesis test.

- **We couldn't do it, and no one else has tried that we know.**

To perform the test requires:

- ***alternative*** **hypotheses that use**
- ***finite*** **portfolios that contain**
- **firms in *diverse* rating grades and loans with *diverse* seniority and security.**

We go through these points in order.

Alternative hypotheses

Alternative Hypothesis

The Alternative LGD function has an additional parameter. That parameter has three nice properties.

- **It controls the sensitivity of cLGD to cPD.**
  - **Sensitivity is the only thing that matters to the function, as you saw.**
- **It controls _*only*_ the sensitivity of cLGD to cPD.**
  - **Neither expected loss (EL) nor the distribution of cPD are affected by the value of the additional parameter. Just the LGD function.**
- **At some value of the parameter, the Alternative equals F-J.**

Spoiler: When the extra parameter is fit by MLE, its value does not differ significantly from zero.

- **The simpler Null hypothesis is not rejected.**
- **That's why the F-J LGD function is considered useful.**

Alternative: Steps 0 and 1

Step 0: Let r symbolize cPD. Let $cLGD[\cdot]$ be the Frye-Jacobs LGD function. The mathematical expectation of cLoss is EL:

$$EL = \int_0^1 r\, cLGD[r]\, pdf_{cPD}[r, PD, \rho] dr$$

$$= \int_0^1 \Phi\left[\Phi^{-1}[r] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[EL]}{\sqrt{1-\rho}}\right] pdf_{cPD}[r, PD, \rho] dr$$

Step 1: That equation holds for any value of EL, such as ψ:

$$\psi = \int_0^1 \Phi\left[\Phi^{-1}[r] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[\psi]}{\sqrt{1-\rho}}\right] pdf_{cPD}[r, PD, \rho] dr$$

Alternative: Steps 2-4

Step 2: Multiply by ELGD*ᵃ*, where *a* is a real number:

$$\psi\, ELGD^{a} = \int_0^1 ELGD^{a}\, \Phi\left[\Phi^{-1}[r] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[\psi]}{\sqrt{1-\rho}}\right] pdf_{cPD}[r, PD, \rho]\, dr$$

Step 3: Set ψ = EL / ELGD*ᵃ*; the left side is now EL:

$$EL = \int_0^1 ELGD^{a}\, \Phi\left[\Phi^{-1}[r] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[EL/ELGD^{a}]}{\sqrt{1-\rho}}\right] pdf_{cPD}[r, PD, \rho]\, dr$$

Step 4: The expectation of this is EL! This must be cLoss!

$$cLGD[cPD, a] = ELGD^{a}\, \Phi\left[\Phi^{-1}[cPD] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[EL/ELGD^{a}]}{\sqrt{1-\rho}}\right] / cPD$$

$$\mathbf{c}LGD = ELGD^{a}\, \Phi\left[\Phi^{-1}[cPD] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[EL/ELGD^{a}]}{\sqrt{1-\rho}}\right] / cPD$$

We just showed that E [this expression * cPD] = EL.

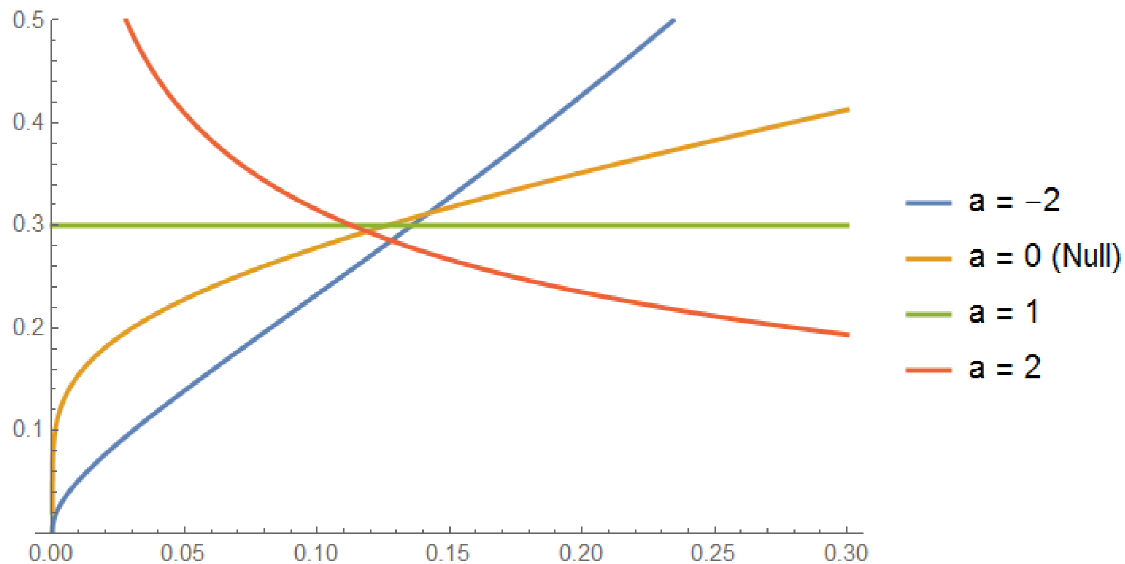
Therefore, this expression is an LGD function.

The next slide shows that the parameter "a" controls the sensitivity of cLGD to cPD…

$$cLGD = ELGD^{a}\,\Phi\left[\Phi^{-1}[cPD] - \frac{\Phi^{-1}[PD] - \Phi^{-1}[EL/ELGD^{a}]}{\sqrt{1-\rho}}\right]/cPD$$

- **If a = 0, this is the Frye-Jacobs LGD function.**
  - **The Null Hypothesis nests with the Alternative.**
- **If a = 1, this is cLGD = ELGD.**
  - **cLGD can be a constant function and independent from cPD.**

Other values give a monotonic-looking function. →→→→



Summary: Alternative A

We have an alternative LGD function with the new parameter, a, which controls the sensitivity of cLGD.

- **a has no effect on EL or on the distribution cPD.**
- **It affects only the relationship between cPD and cLGD.**

If a significantly different from 0, we reject Frye-Jacobs.

- **It isn’t and we don’t.**

If significantly different from 1, we reject fixed cLGD.

- **It is and we do.**
  - **One can't assume that an implausible hypothesis is true, simply because the available data don’t allow rejection in a particular model framework.**

    I can’t reject the null hypothesis that vaccines are worthless, but it hardly proves that they are.
  - **The data confidently reject H_0: cLGD does not depend on conditions.**

Questions?

Finite portfolios

Finite portfolio

A finite portfolio introduces randomness into the default rate and into average LGD.

We assume that the finite portfolio is *uniform*:

- **All loans in the portfolio have equal PD and equal ρ.**

The number of defaults is *Binomial* with mean equal cPD.

  - **Same as when we derived the PMF of the number of defaults on Week 1.**

We assume each LGD is normally distributed around cLGD:

- $LGD_i \sim N\left[\, cLGD[cPD, a], \sigma^2 \right]$ **using the Alternative LGD function.**
- **We assume σ = 20%. This is about what you estimate in data.**
- **Normality is convenient because we take averages.**
  - **The average of two normal variables is a normal variable.**
  - **Among useful distributions, only the normal has this property.**

Symbols

We are deriving the distribution of portfolio credit loss. (Given the name of this course, it is about time.)

We define these symbols:

- **N: The number of firms in the portfolio.**
- **D: The number of defaults among the N firms.**
- **LGD: The *average* LGD rate among the D defaults.**
- **Loss: The portfolio loss rate.**
  - **Loss = LGD * D / N.**
- **cLGD and cPD are conditional expectations as always.**

If there is no default, there is no loss…

Point mass at zero loss

The probability of zero defaults among N loans is:

$$\int_0^1 (1 - cPD)^N \, pdf_{cPD}[cPD] \, dcPD$$

where $pdf_{cPD}[cPD]$ is the Vasicek PDF.

Example calculation: If N = 10, PD = 0.1, ρ = 0.15, then the probability of zero defaults is 0.431.

- **Try it and see!**

Loss when D > 0

We seek the distribution of Loss for a portfolio of N loans that has D > 0 defaults. We assume that the LGD of each defaulted loan is normal:

$$LGD_i \sim \text{IID}\ N\,[\,cLGD[\,cPD, a\,]\,, \sigma^2]$$

Then, portfolio average LGD is also normal:

$$LGD \sim N\,[\,cLGD[\,cPD, a\,]\,, \sigma^2/D]$$

This is the distribution of portfolio average LGD,

- ***conditioned*** **on the random number of defaults, D, and**
- ***conditioned*** **on random cPD.**

Conditioned on D and cPD…

Infer the distribution of Loss from the distribution of LGD:

$$LGD|cPD, D \sim N\,[\,cLGD[\,cPD, a\,]\,, \sigma^2/D]$$

$$LGD = cLGD[cPD, a] + \frac{\sigma}{\sqrt{D}}Y, \quad Y \sim N[0,1]$$

$$Loss = \frac{D}{N}LGD = \frac{D\;cLGD[cPD, a] + \sqrt{D}\,\sigma\,Y}{N}$$

Invert: $Y = \frac{N\;Loss - D\;cLGD[cPD, a]}{\sigma\sqrt{D}}\;;\;\frac{\partial\,Y}{\partial\;Loss} = \frac{N}{\sigma\sqrt{D}}$

$$pdf_{Loss|D,cPD}[Loss] = \frac{N}{\sigma\sqrt{D}}\,\phi\left[\frac{N\;Loss - D\;cLGD[cPD, a]}{\sigma\sqrt{D}}\right]$$

Remove the conditioning

The next step resembles finding the PMF of the number of defaults in a finite portfolio, as in Week 2.

The derivation expresses the PDF of Loss in terms of

- **the PDF of Loss given D and cPD (found on the last slide),**
- **the PDF of D (the number of defaults) given cPD, and**
- **the PDF of cPD, which is the Vasicek PDF.**

$$pdf[Loss]$$

$$= \int pdf[Loss, cPD]\; dcPD$$

$$= \int \overbrace{pdf[cPD]\;\; pdf[Loss|cPD]}\; dcPD$$

$$= \int pdf[cPD] \overbrace{\sum_{D=1}^{N} pdf[Loss, D|cPD]}\;\; dcPD$$

$$= \int pdf[cPD] \sum_{D=1}^{N} \overbrace{pdf[Loss|D, cPD]\; pmf[D|cPD]}\;\; dcPD$$

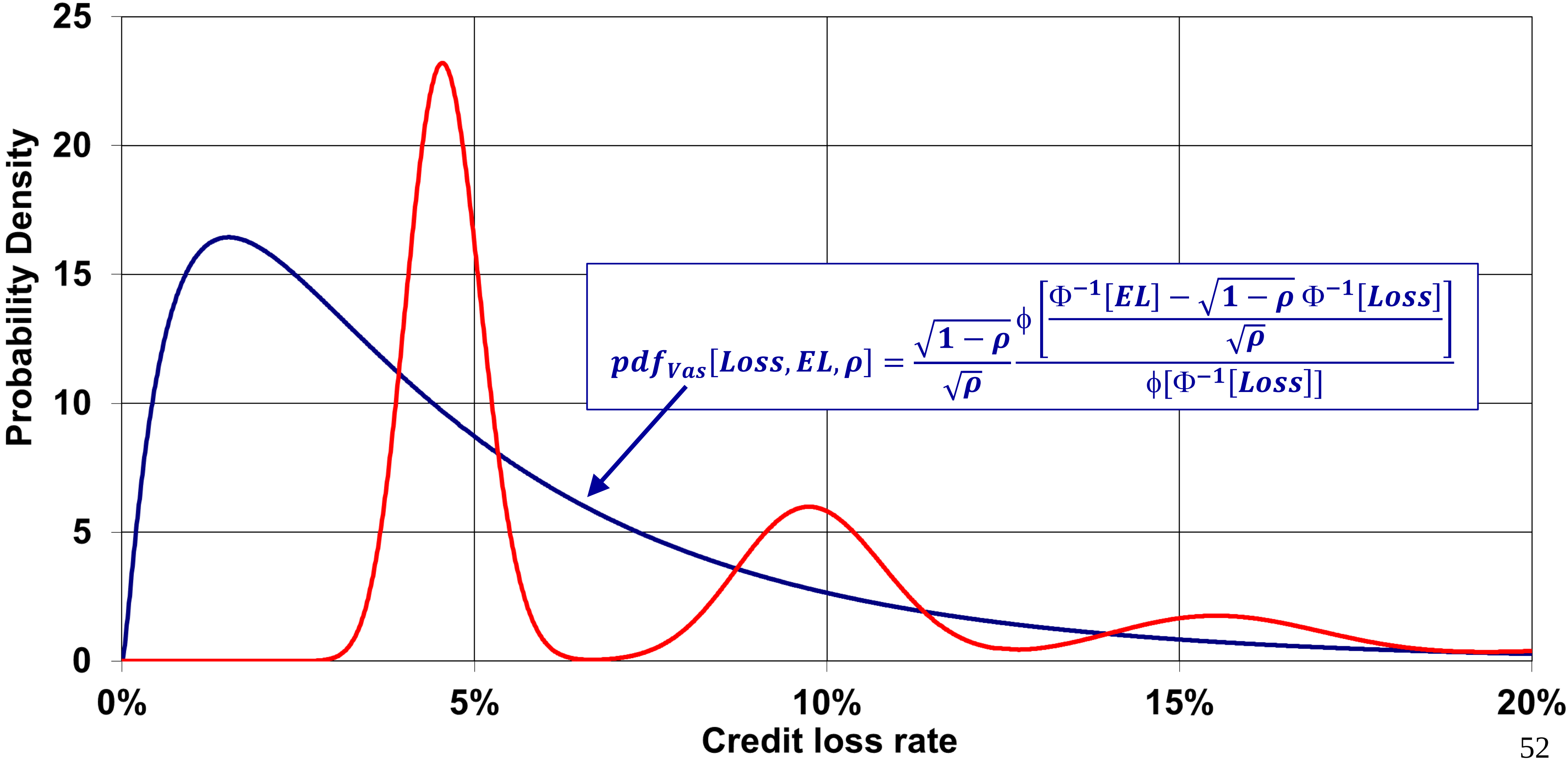
$$= \int pdf_{Vas}[cPD] \sum_{D=1}^{N} \overbrace{\frac{N}{\sigma\sqrt{D}}\;\; \phi\left[\frac{N\; Loss - D\; cLGD[cPD, a]}{\sigma\sqrt{D}}\right]} \overbrace{\binom{N}{D} cPD^{D}\; (1 - cPD)^{N-D}}\;\; dcPD$$

This the distribution of loss each period of one year.

Distribution of loss in a finite portfolio

N=10, PD=10%, EL=5%, ρ =15%, σ =1%, a =0; Pr[D=0]=0.431

$$\int pdf_{Vas}[cPD] \sum_{D=1}^{N} \frac{N}{\sigma\sqrt{D}}\ \phi\left[\frac{N\ Loss - D\ cLGD[cPD,a]}{\sigma\sqrt{D}}\right]\binom{N}{D} cPD^{D}\,(1-cPD)^{N-D}\ \ dcPD$$



Summary: Finite portfolio

In a finite portfolio, the default rate has expectation equal to cPD and the LGD rate has expectation equal to cLGD.

- **The number of defaults has a Binomial distribution.**
- **LGDs are assumed normally distributed around cLGD.**

The resulting distribution of Loss in a finite portfolio is quite a lot more complicated than the Vasicek distribution.

In practice the most difficult step was to find an alternative hypothesis that changed the steepness of the LGD function without affecting EL.

As always, this model is wrong. There isn't enough data to show that it is wrong and to suggest something better.

Questions?

The tests and summary

Multiple grades and classes

There are 5 rating grades and 5 seniority classes.

We assume a single risk factor, Z.

- **As before, the losses within different grades and classes are *conditionally* *independent*.**
  - **We perform change-of-variable to get all losses as functions of Z.**
  - **We integrate over Z rather than cPD.**
  - **We multiply PDFs of the sub-portfolios to produce the integrand.**
  - **This is messy to write down on a slide, but you get the idea.**

Doing this lets us analyze all loans together, all bonds together, or all instruments together.

One test

For both the Null and the Alternative:

- **PD and ρ are set to MLE's based on *<u>default</u>* data.**
- **ELGD equals average LGD in each grade – class combo.**
- **σ is set to 20%**
  - **This is on the low side. I am *<u>not</u>* packing the model with false noise.**

H_0: $a = 0$; Frye-Jacobs explains the data.

H_1: a equals its MLE based on the loss data.

- **The sensitivity of cLGD to cPD is different from Frye-Jacobs.**

Result: MLE [a] = 0.01

MLE [a] = 0.01 for all loans taken together.

- **a = 0.01 is not significantly different from a = 0.**
  - **The Frye-Jacobs LGD function is not rejected.**
- **a = 0.01 is significantly different from a = 1.**
  - **The idea that LGD is fixed is rejected**
  - **LGD varies with the default rate.**

Most papers show estimates *<u>different</u>* from zero.

- **The paper's pet idea is shown to reject an idea that has been rejected many times before, such as that certain macro variables are completely independent.**

We show that there is no value of a that does a significantly better job modeling cLGD.

- **We conclude that F-J is consistent with Moody's.**

Summary: ***An*** LGD function

Assumption: If a set of conditions are expected to make the default rate go up, they should be expected to make the Loss rate go up.

- **cPD and cLoss are comonotonic.**

Implication: Every loan has an LGD function that maps its cPD to its cLGD.

- **The function depends on two distributions.**
  - **There is no limit to the complexity of either one.**

Summary: ***The*** LGD function

Frye and Jacobs find an LGD function that is strictly monotonic for all values of PD, EL, and ρ.

An Alternative LGD function contains a parameter that controls the sensitivity of cLGD to cPD.

The sensitivity parameter is *not* significantly different from zero.

The Fed uses F-J in stress testing:
https://www.federalreserve.gov/publications/files/2022-march-supervisory-stress-test-methodology.pdf

References

Jon.Frye@chi.frb.org

Frye, Modest Means, *Risk*, January 2010.

- **A two-parameter credit loss distribution is adequate, given Altman's data. The LGD function is later inferred from this idea.**

Frye and Jacobs, Credit loss and systematic loss given default, *Journal of Credit Risk*, Spring 2012

- **The sensitivity of cLGD to cPD calibrated to Moody's data is nearly equal to the sensitivity built into the LGD function.**

Frye, The link from default to LGD, *Risk*, March 2014

- **Tail LGD is better predicted by the LGD function than by linear regression using simulated data from a linear model.**

Questions?

Don’t forget

Homework 4 is due next week at 6PM.

Lisheng’s TA session will be Sunday at 6PM.