The Link from Default to LGD

IACPM

Washington, DC 7 November 2013

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It is easier if you Google me

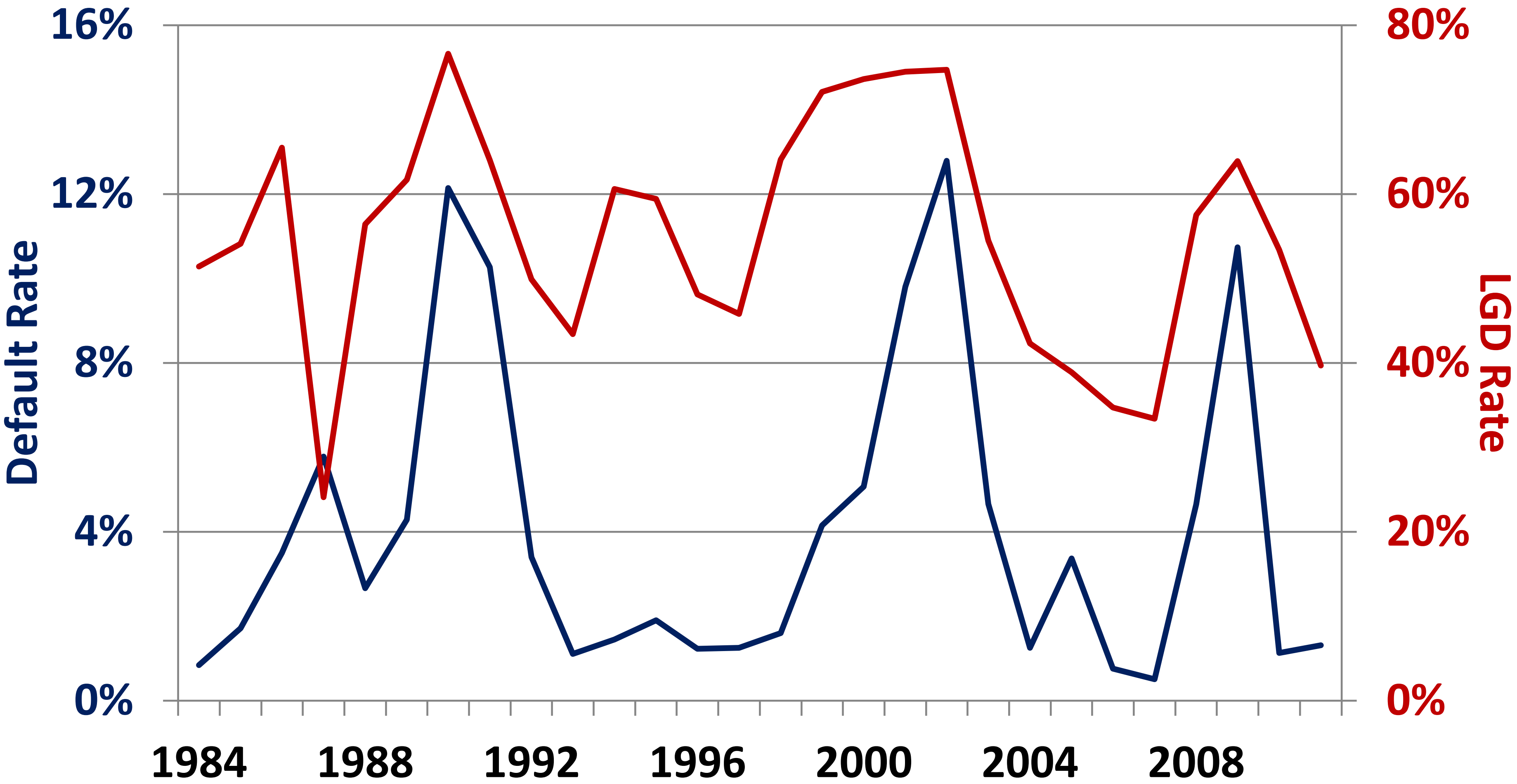
Topics

Modeling challenge: when the default rate is high, the loss given default (LGD) rate is also high. (1 slide)

Modeling answer: The LGD function (1 slide)

- **It works better than statistical analysis of data. (11 slides)**
  - **It is likely to work better for a long time. (1 slide)**
- **It survives testing with historical data. (4 slides)**
- **If permitted by bank supervisors, with a small modification it can be used for stress testing. (5 slides)**

When DR is high, LGD is high



Source: Altman-Kuehne High-Yield Bond Default and Return Report, February 2012

The Frye-Jacobs LGD function

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

$\Phi[\,\cdot\,]$ = Cumulative Distribution Function of Standard Normal

The LGD function applies to every loan at every bank.

- **The value of ρ doesn't have much effect; ρ = 10% should work OK.**
- **PD and EL (EL = PD * ELGD) are expectations.**
    - **A bank should already estimate these, especially EL.**
- **cLGD and cDR are the rates to be expected under *conditions,* such as a recession, the 98th %ile, etc.**
    - **Put in a possible default rate; the function tells LGD in the same conditions.**

The LGD function has a moderate upward slope.

Conditions that produce high default rates produce high LGD rates.

It works better than regression

This probably sounds surprising.

Usually, people think that regression produces good results.

I show the contrary using simulated LGD data.

With simulation, I know the right answers,

so it is easy to judge which method works better.

I show three specific cases to illustrate what happens.

Then I summarize 10,000 random simulation runs.

Then I simulate under completely different conditions.

So don't be too concerned if the first situation seems different from the kind of lending that you do.

Welcome to my simulation

Simulation is a random draw from a distribution.

Let's pick a distribution.

NOT because I believe it is realistic. *I don't*.

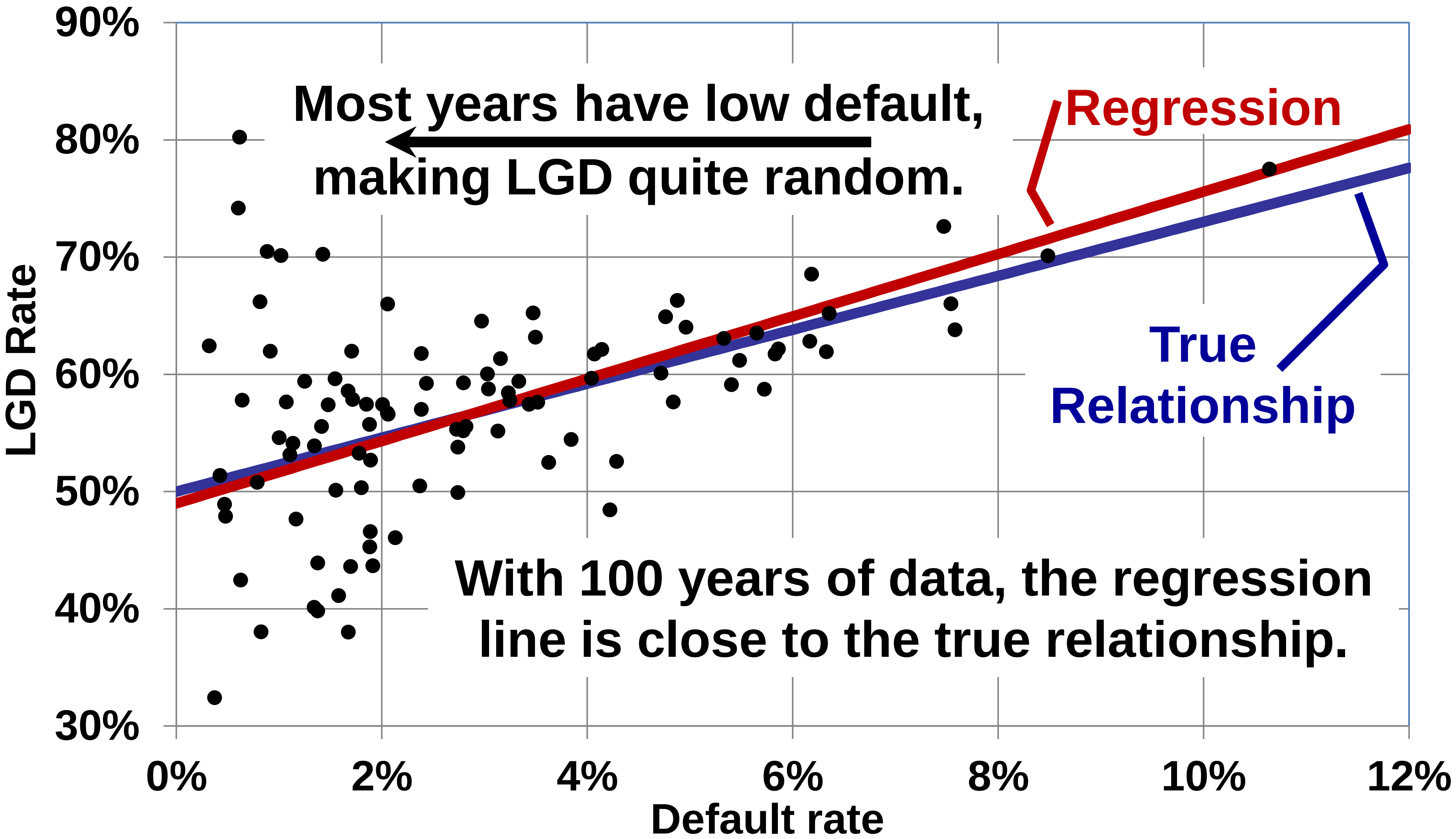
This is just one of the *many* situations to be tried.

This one does *not* put the LGD function in best light, BTW.

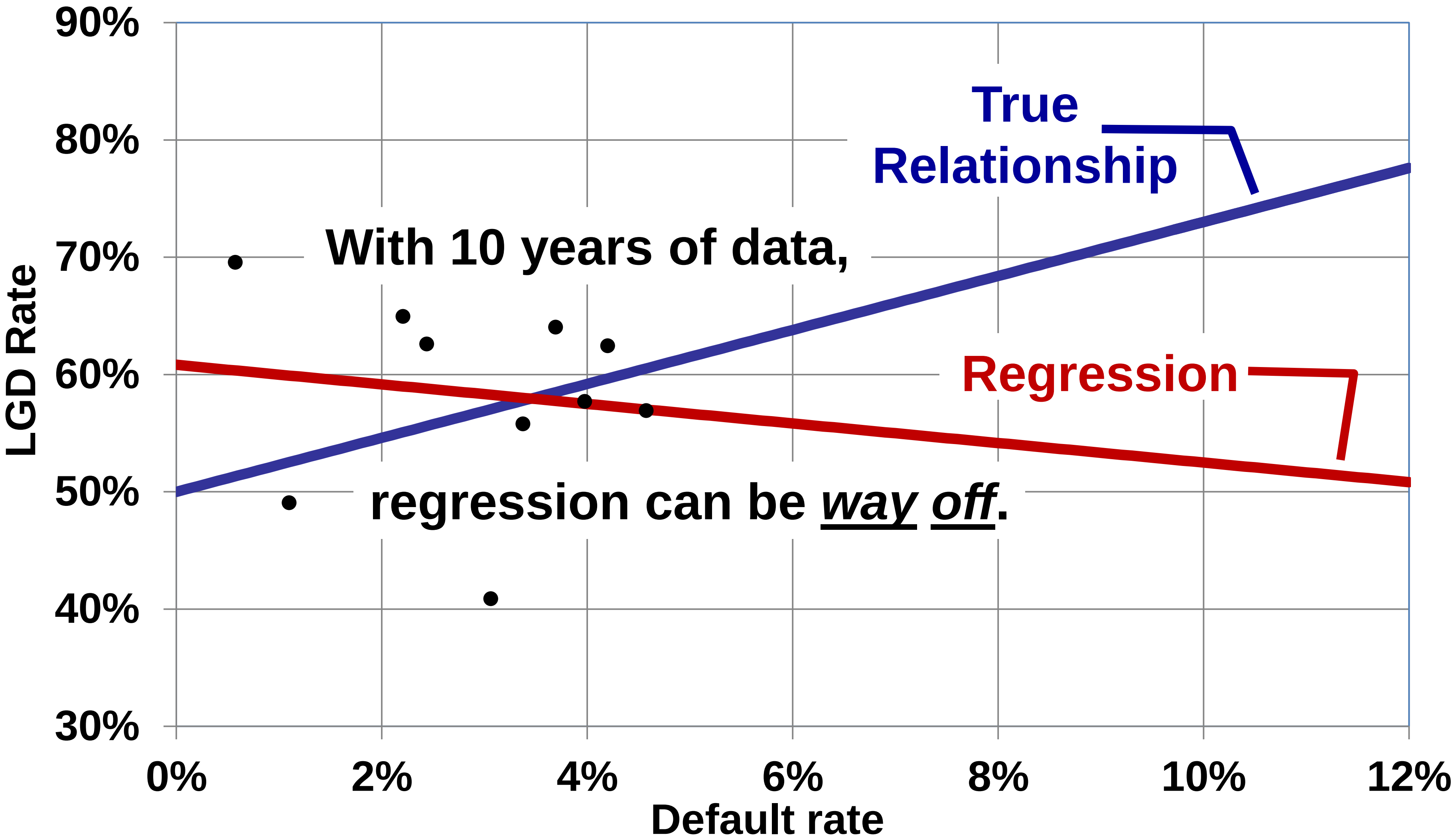
Let's:

- **suppose the true relationship is the blue line on next slide**
- **simulate 100 years of data for a portfolio of 1,000 loans**
- **run a red regression line through the data swarm…**

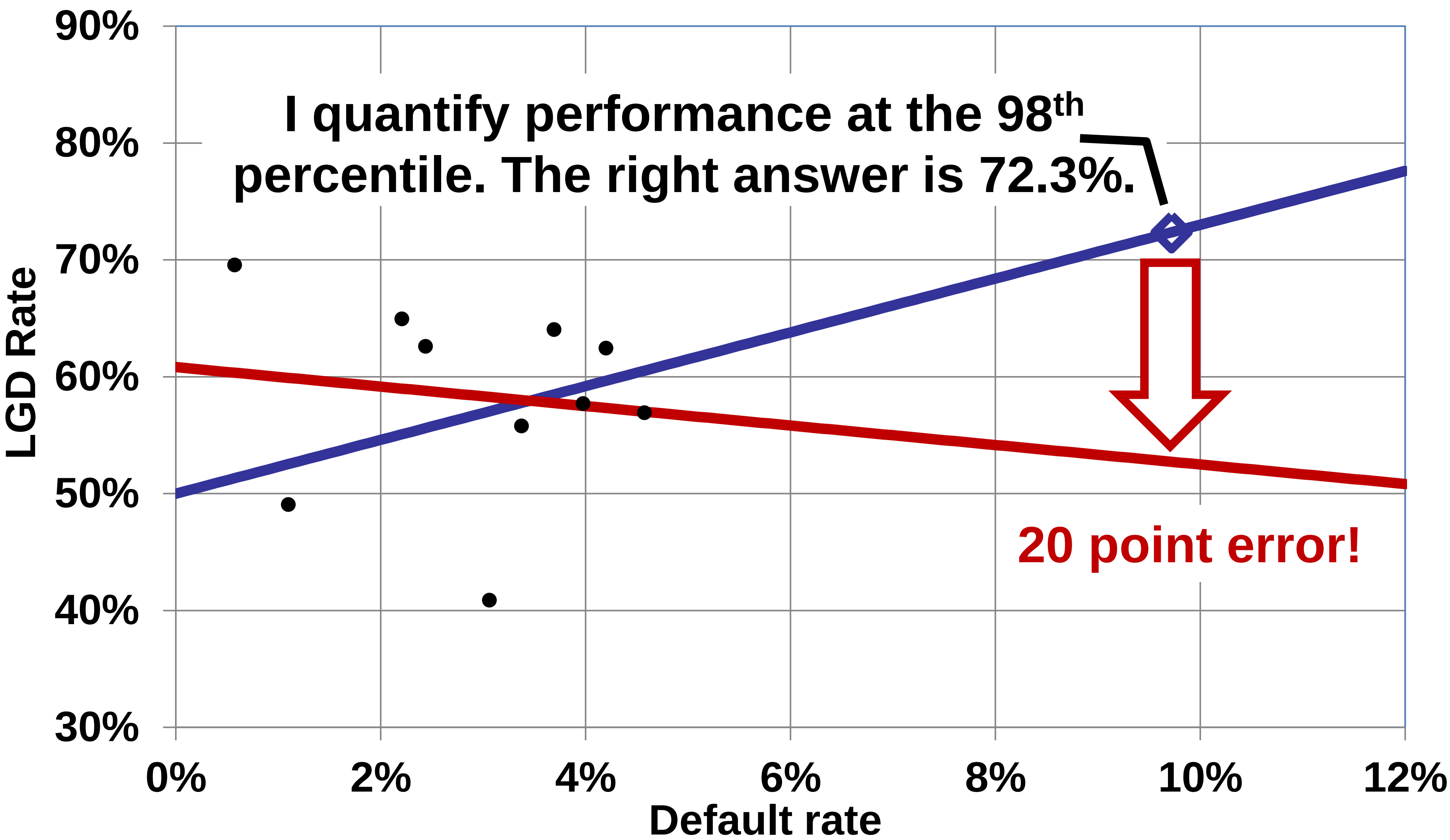
Regression on 100 years of data



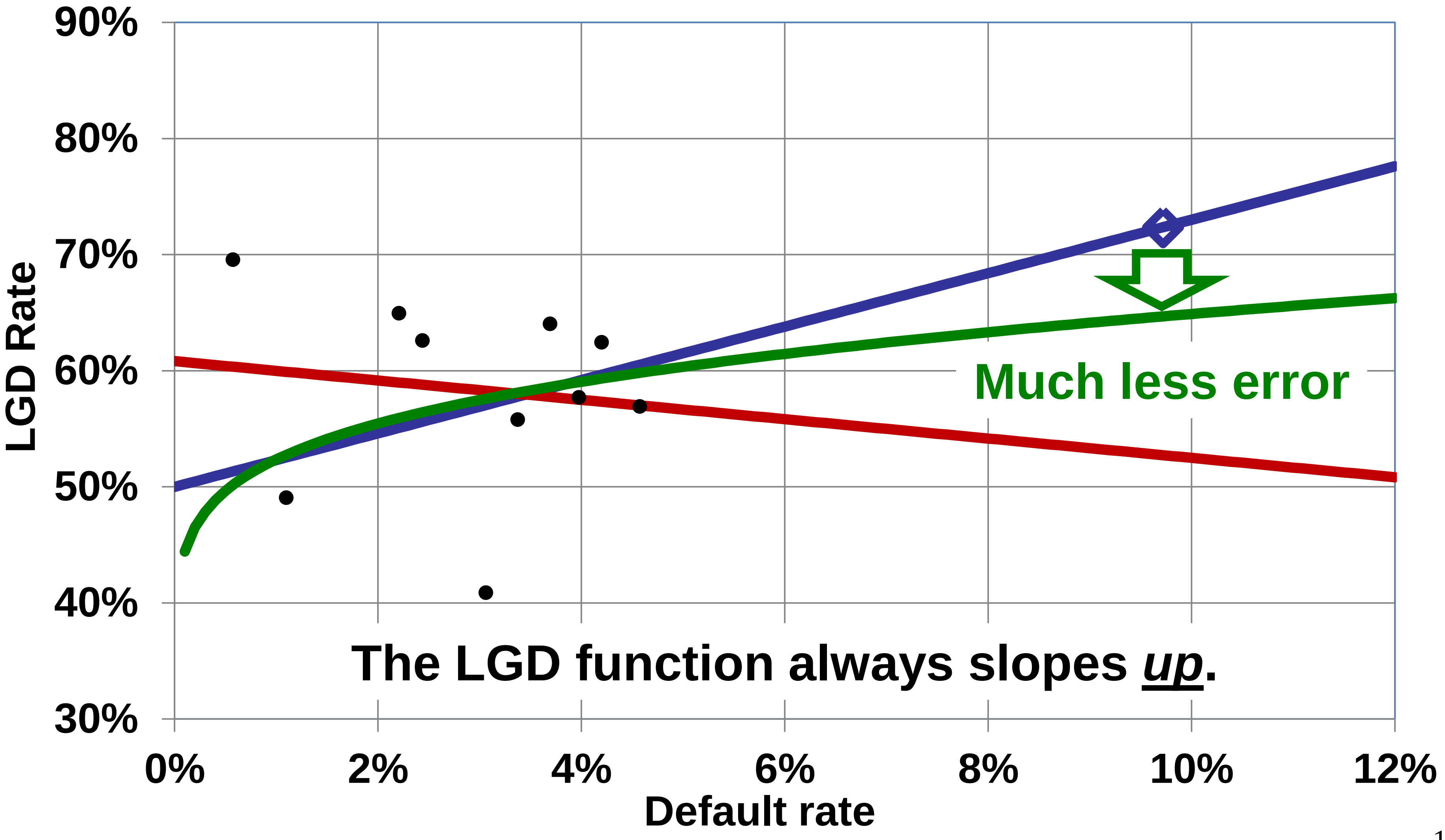
Only 10 years of data: Case 1



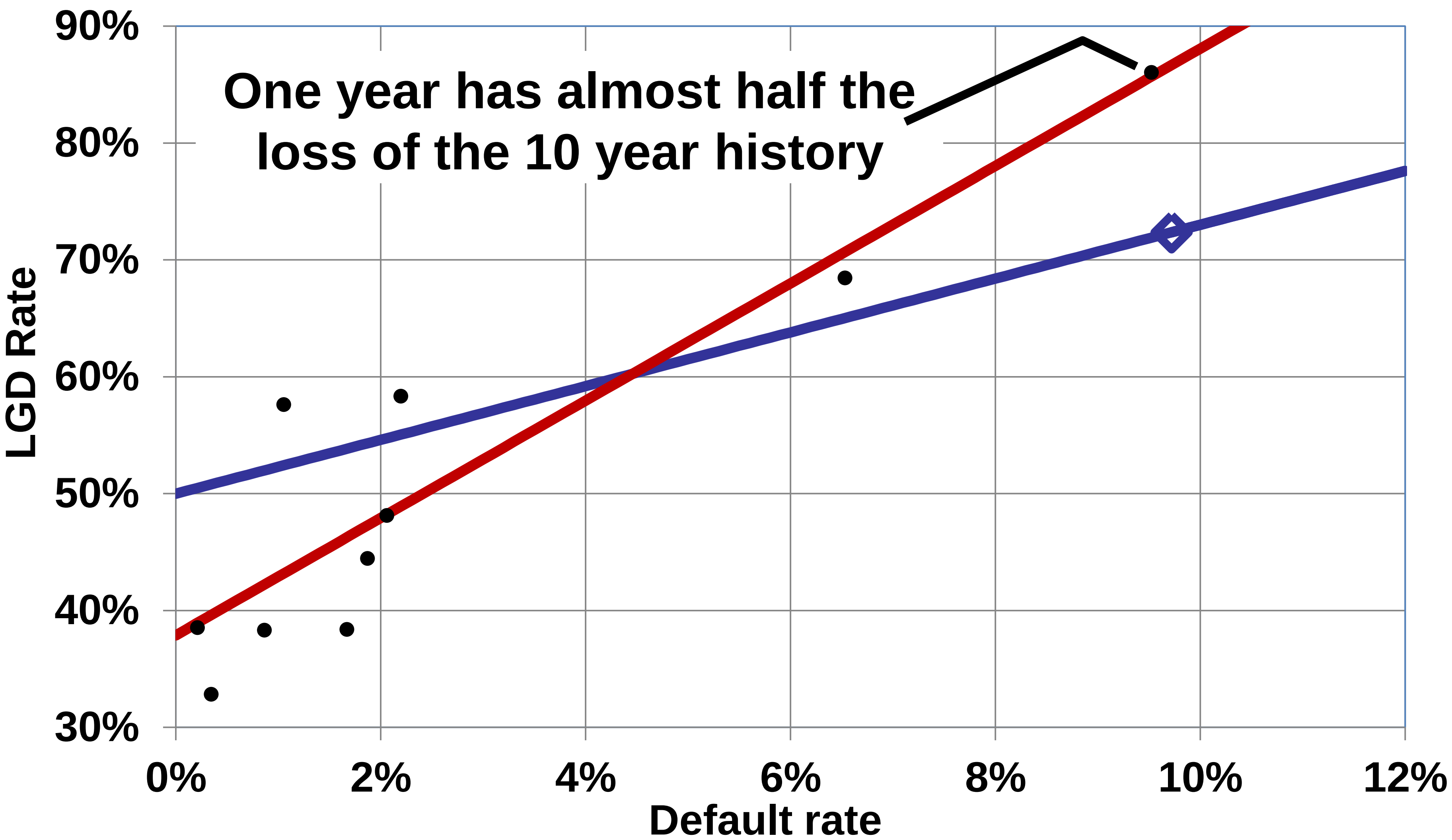
Case 1: Regression performance



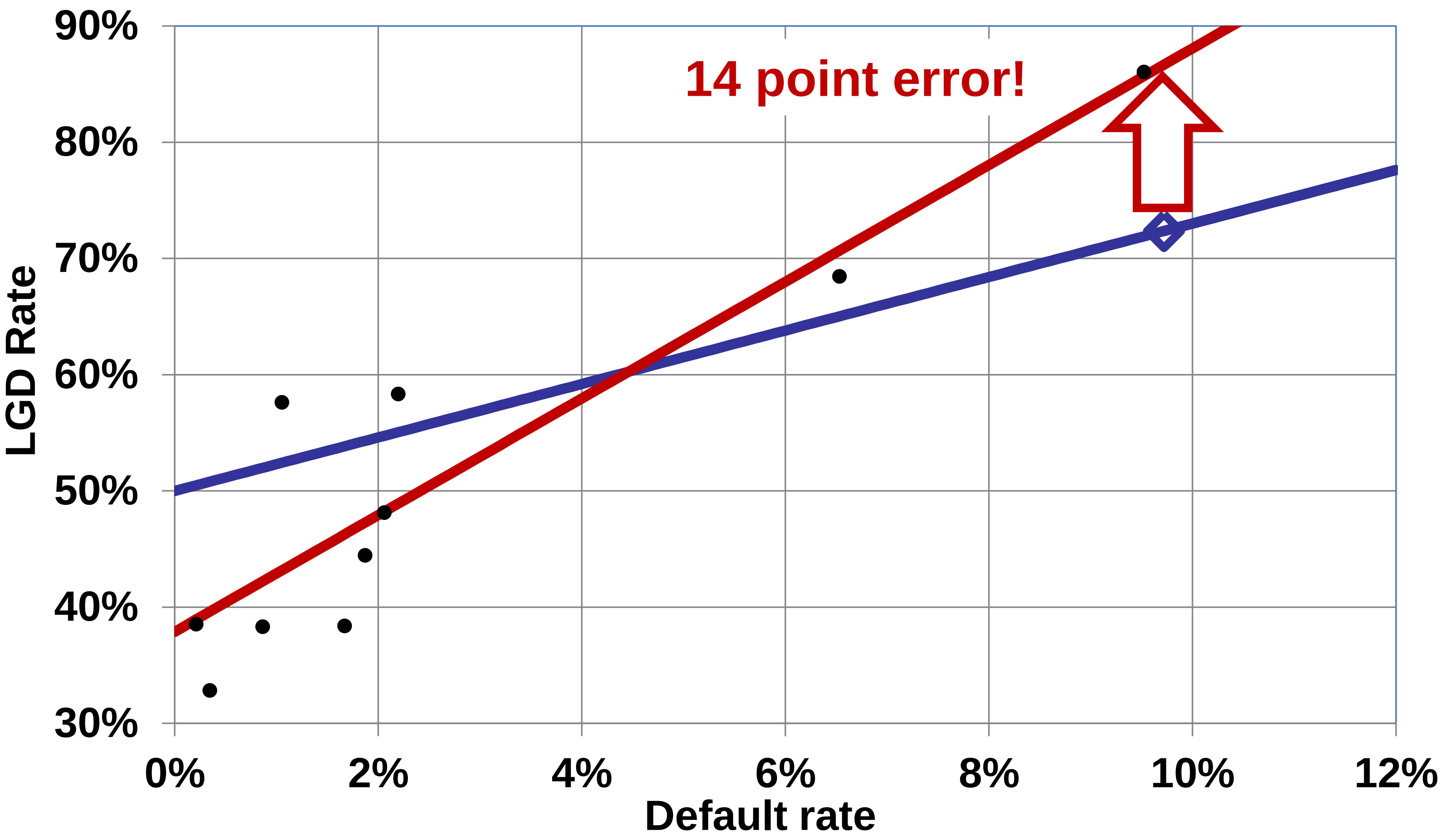
Case 1: LGD function works better



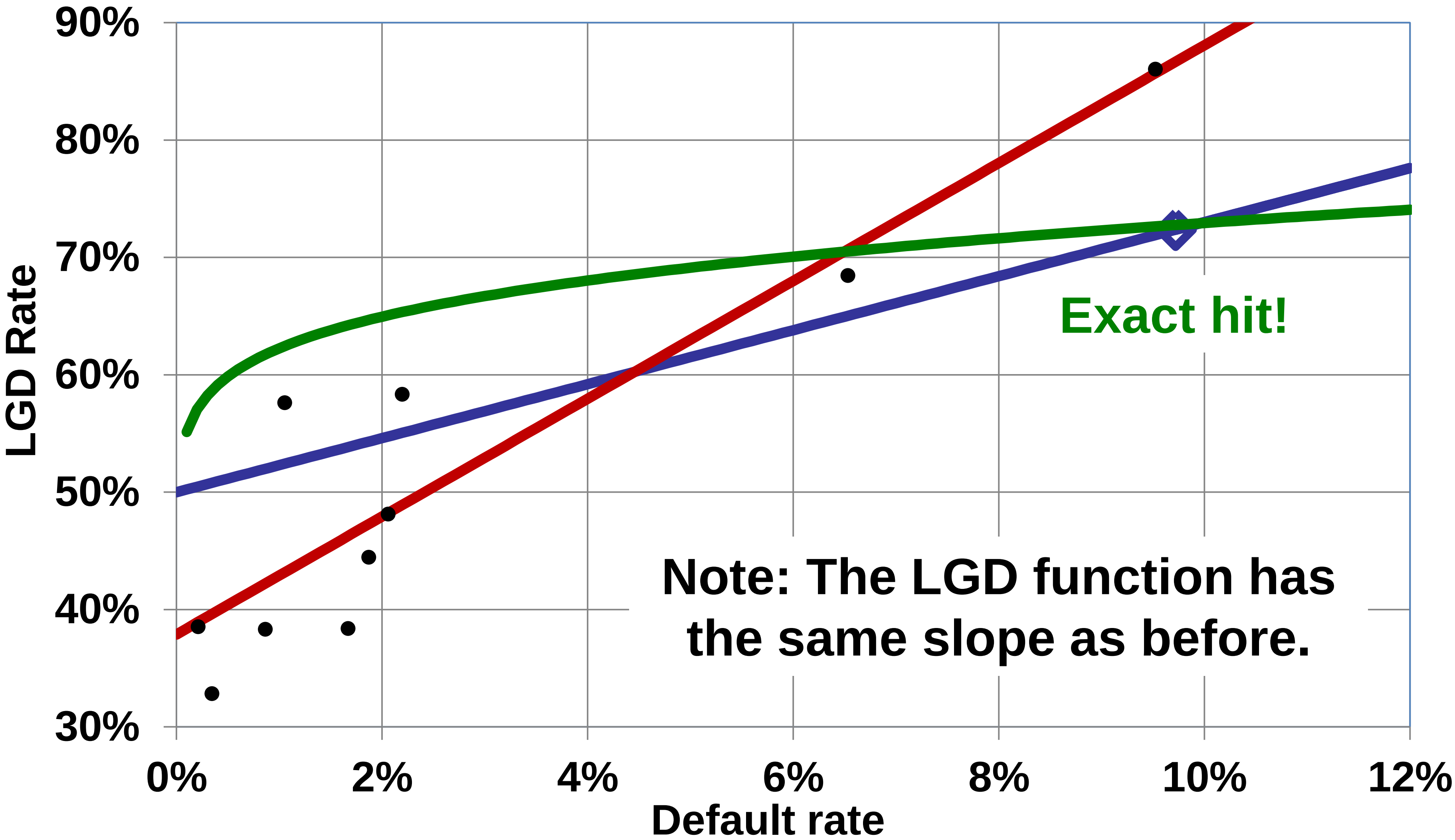
Case 2: The data swarm is steep



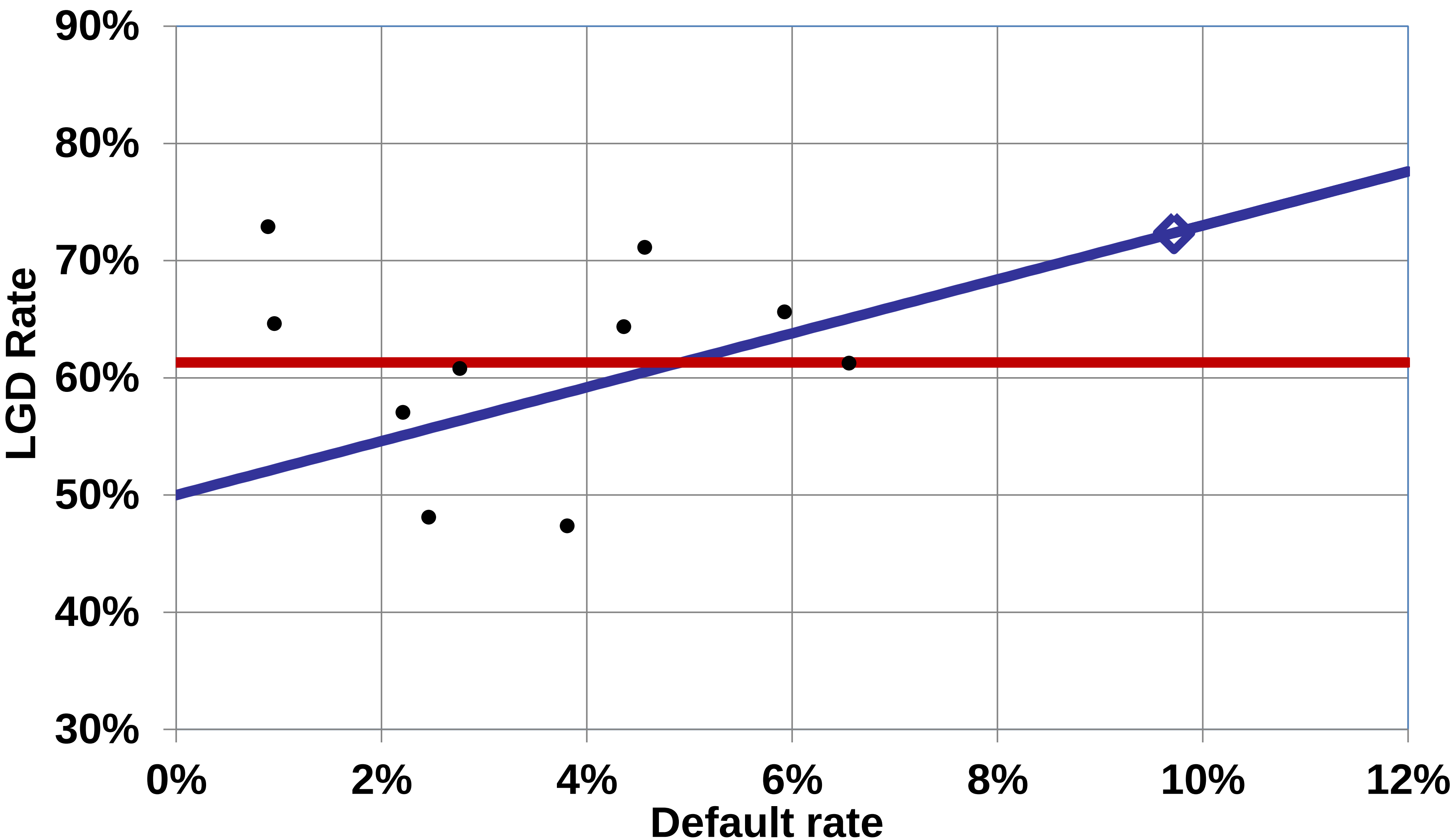
Case 2: Regression performance



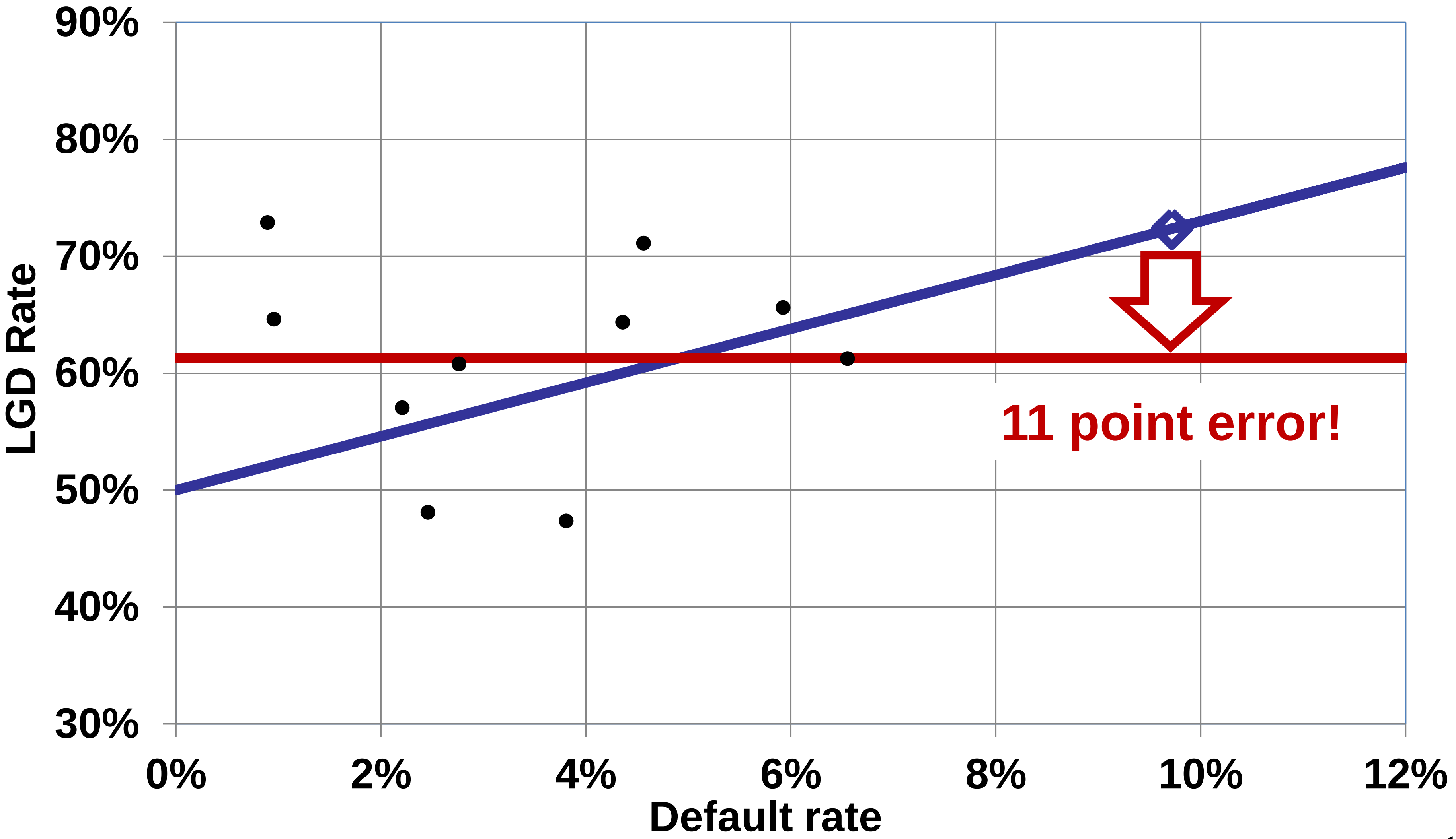
Case 2: LGD function works better



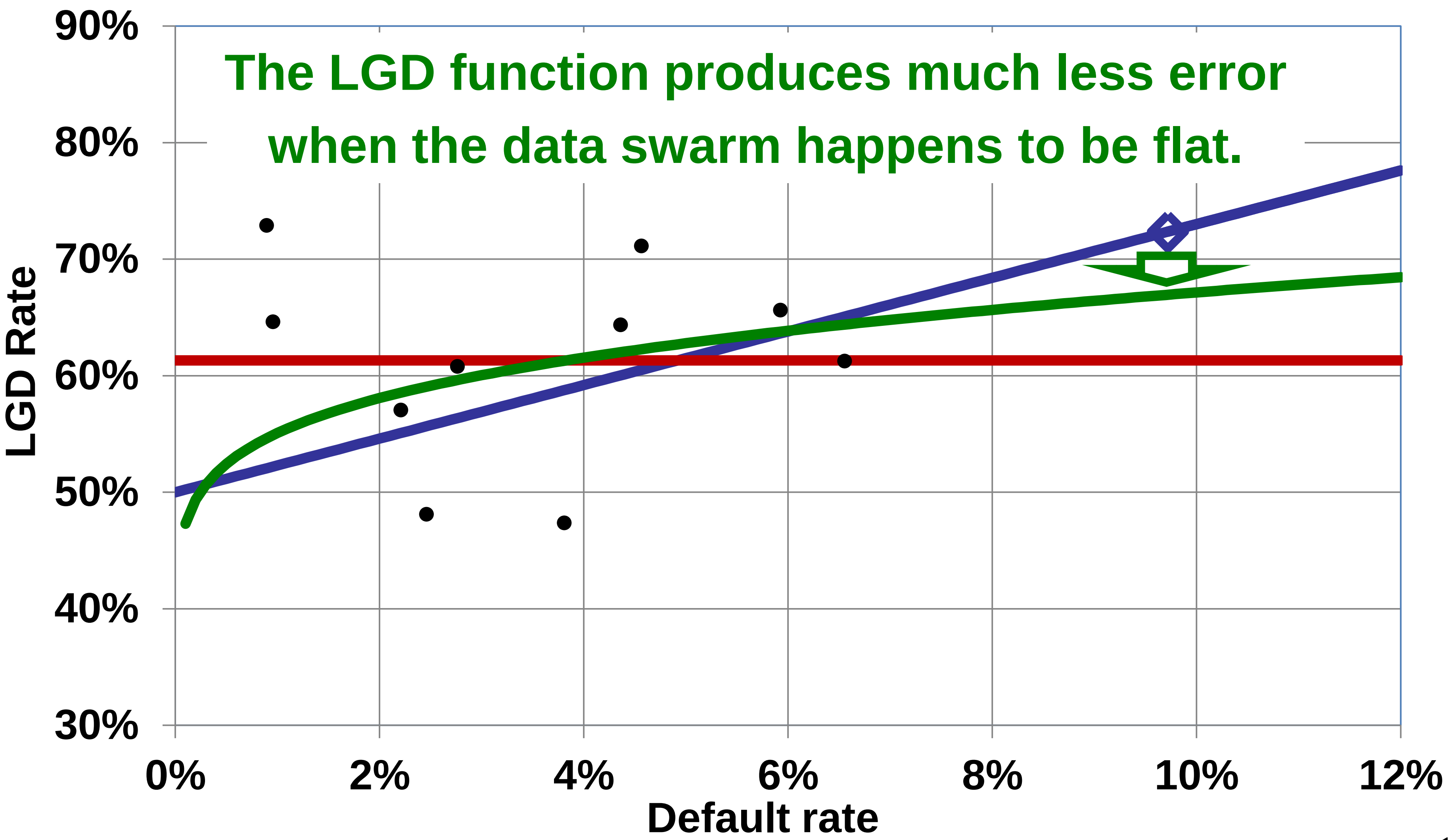
Case 3: The data swarm is flat



Case 3: Regression performance



Case 3: LGD function works better



Regression and the LGD function

- **Regression fits a data set better than the LGD function.**
  - **But you don't want that!**
  - **The data set is short. That tends to *<u>mislead</u>* regression.**
  - **This encourages belief in too much risk or too little risk.**

- **The LGD function doesn't even try to match the slope of the data swarm.**
  - **The LGD function has a moderate upward slope, regardless.**
  - **Only the averages, EL and PD, affect the LGD function.**

- **The LGD function gets closer to the right answer.**
  - **Root mean squared error for regression = 11.0%.**
  - **Root mean squared error for LGD function = 7.9%.**

What about different situations?

I did many more simulation experiments, using a wide range of values for each of the eight control variables:

- **PD, EL, and ρ,**
- **the steepness of the true relationship, standard deviation of individual LGD's, and percentile target for "tail" LGD,**
- **number of firms in portfolio and number of years of data.**

There are only two conditions where regression wins:

- **where there are many *decades* of data or**
- **where the true relationship is *very steep*.**

These conditions *probably do not hold in the real world*.

What about historical data?

The LGD function has been tested on Moody's data.

e.g., 1996-2009 loans rated Ba3, B1, B2, B3, or "C".

An alternative function allows for different slopes,

instead of the slope that is baked into Frye-Jacobs.

The next slide shows ***two*** lines, not one.

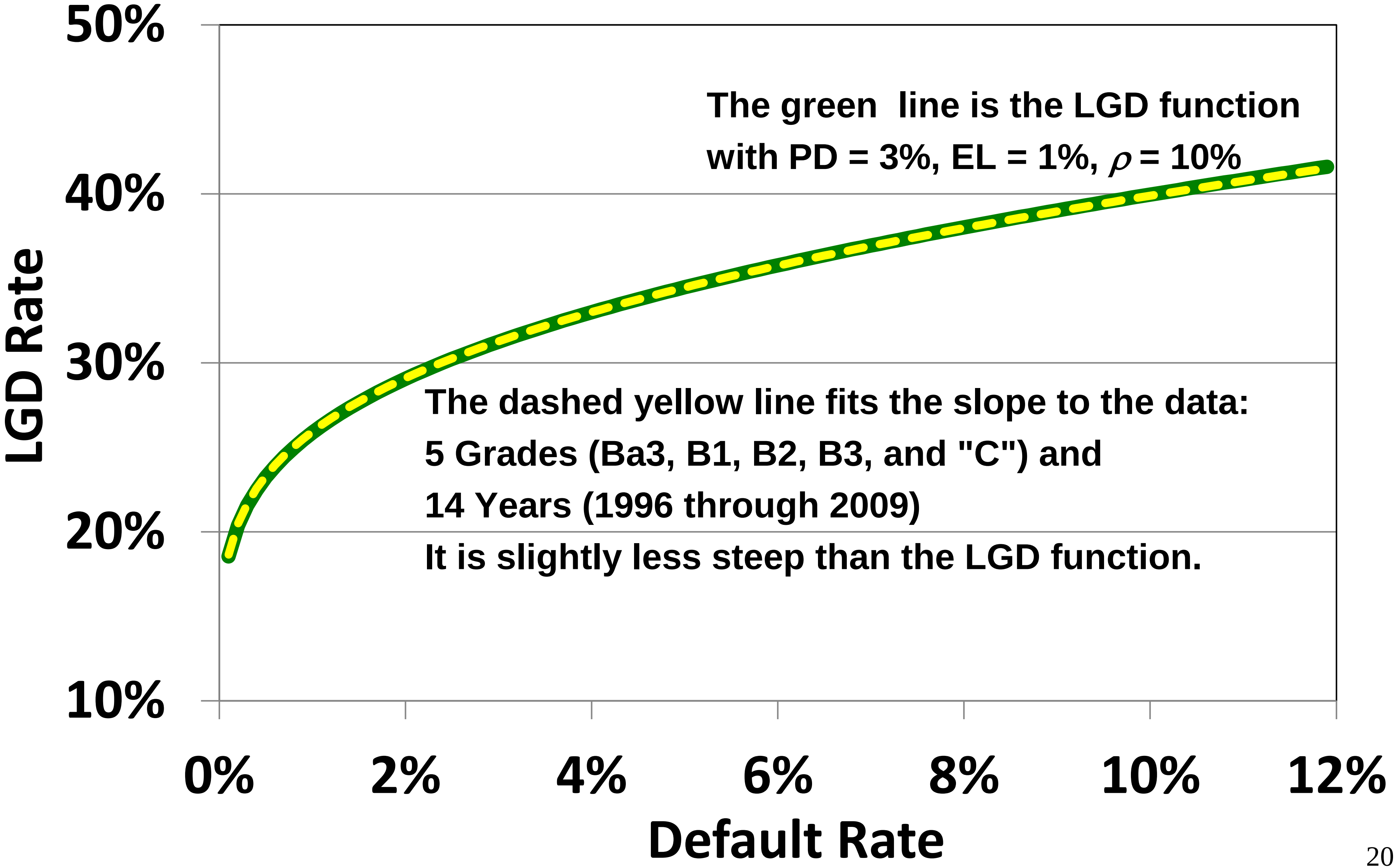
The solid green line is the LGD function.

The dashed yellow line is the MLE of the alternative.

The point is: A different slope is not significant.

The baked-in slope is good enough to describe loan data.

The LGD function fits the data



What about your data or idea?

I admit that I have not tried everything:

- I have not used the data that you have.
- I may not have tried your favorite hypothesis about LGD.
  - For example, "LGD dos not vary with conditions," or
  - "The unemployment rate affects LGD over and above the influence of the default rate."

There is nothing to stop you from testing your idea.

Frye and Jacobs describe exactly how to do the test.

- Their paper is almost entirely an extended attempt to improve upon the LGD function. They couldn't do it.
- It would make my day if someone tries this. Go for it!

Summary: It works

The LGD function outperforms statistical analysis.

> **To beat the LGD function, you need to have great LGD risk and/or a data set that is longer than now available.**

More-complicated models are not significant:

- **for loans, bonds, or all instruments;**
- **for individual combinations of grade and seniority; and**
- **for any of four alternative LGD functions.**

Therefore, a science-based practitioner gives *provisional* *acceptance* to the LGD function.

Dodd-Frank annual stress tests

There is interest in using the LGD function for DFAST.

If supervisors declare the LGD function can be used, a simple modification is required.

Recall:

- **The views I express are mine.**
- **They do not necessarily represent the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.**

Stress tests

Loss depends on a known macroeconomic scenario.

- There is almost no random dispersion in this set-up.

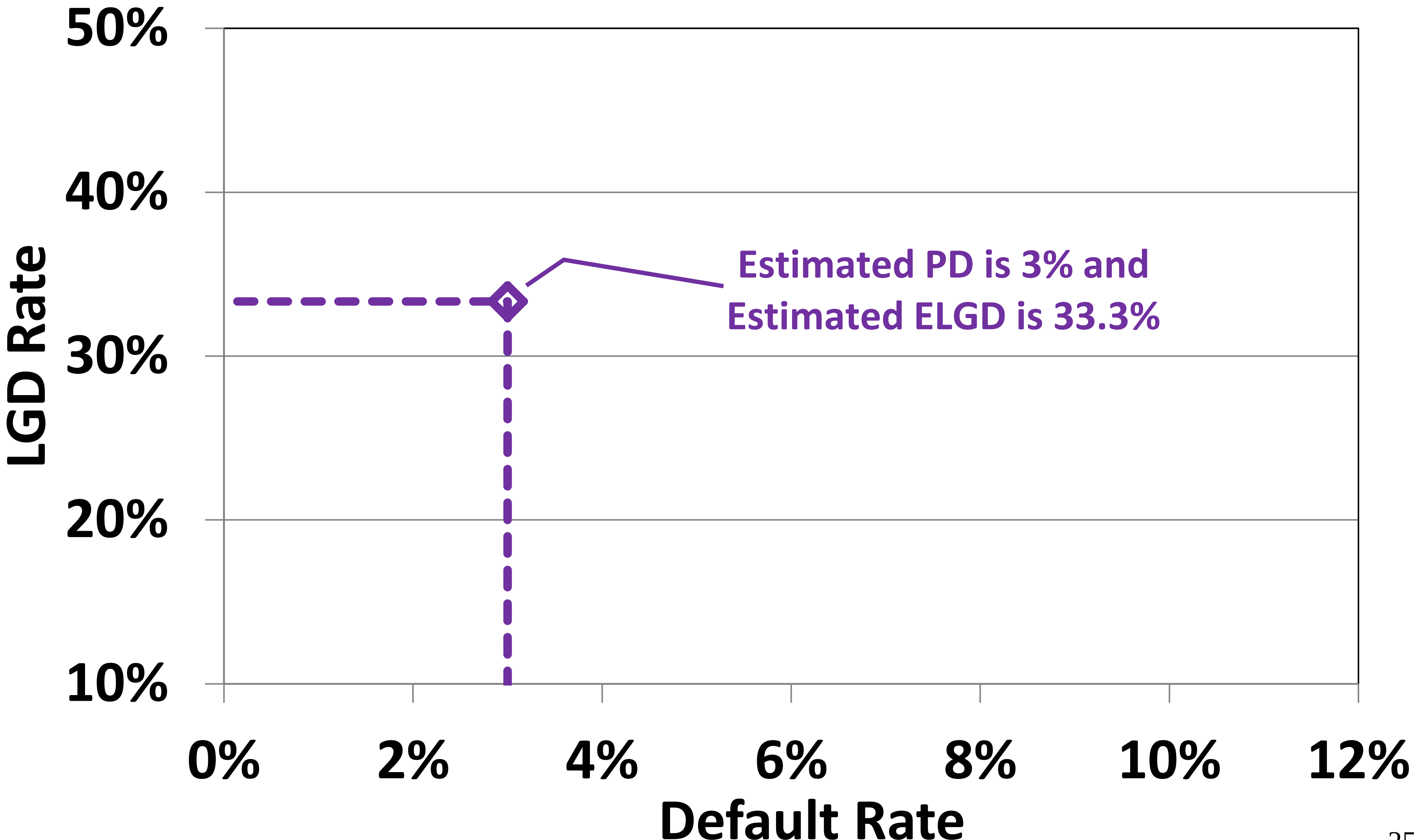
Therefore, a good value of ρ is zero.

As you'll soon see, when ρ is set to zero the loss scenario rides along a fixed LGD function.

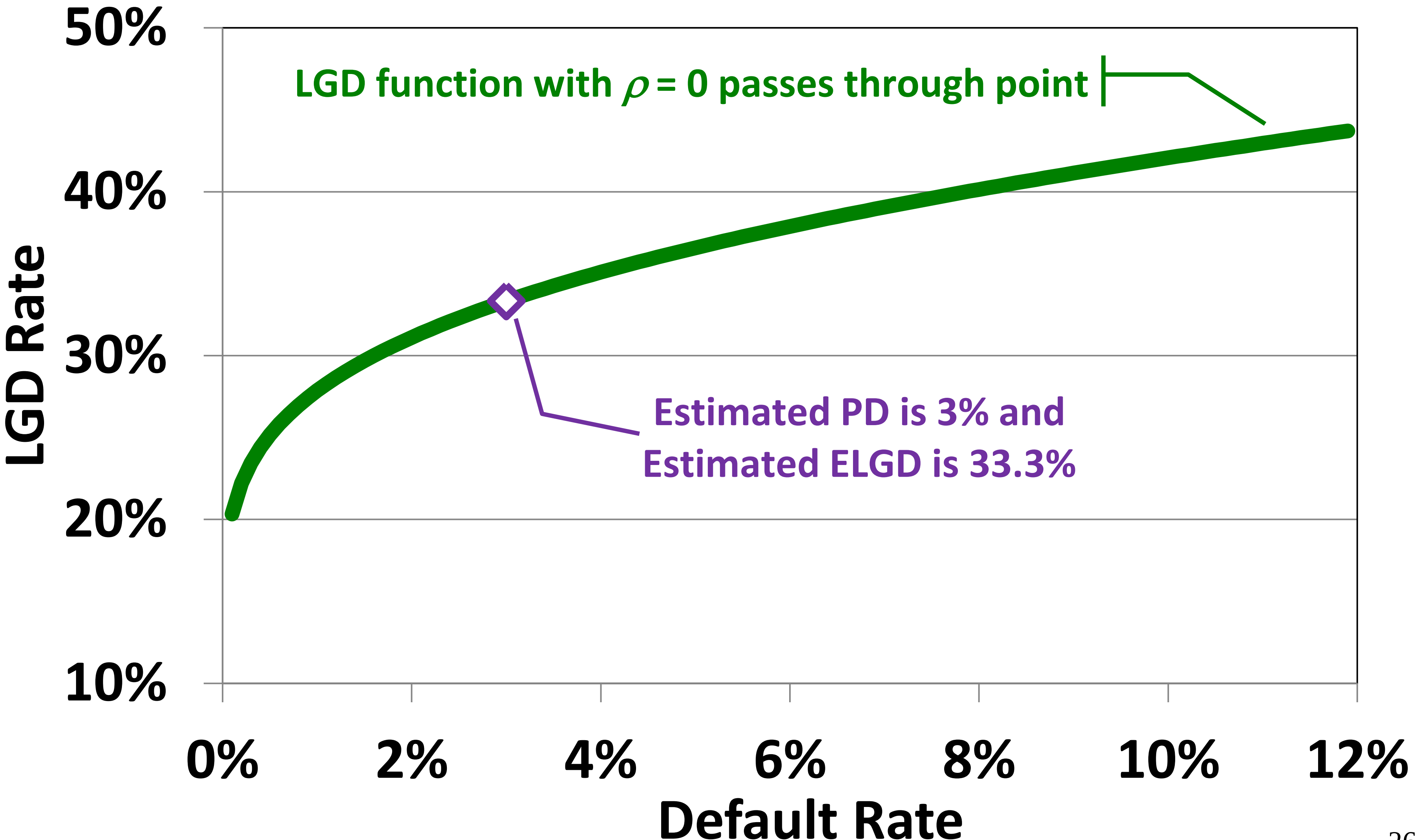
- Stressed PD and stressed loss change from quarter to quarter, but the LGD function stays put.

So, start with a loan's current values of PD and ELGD...

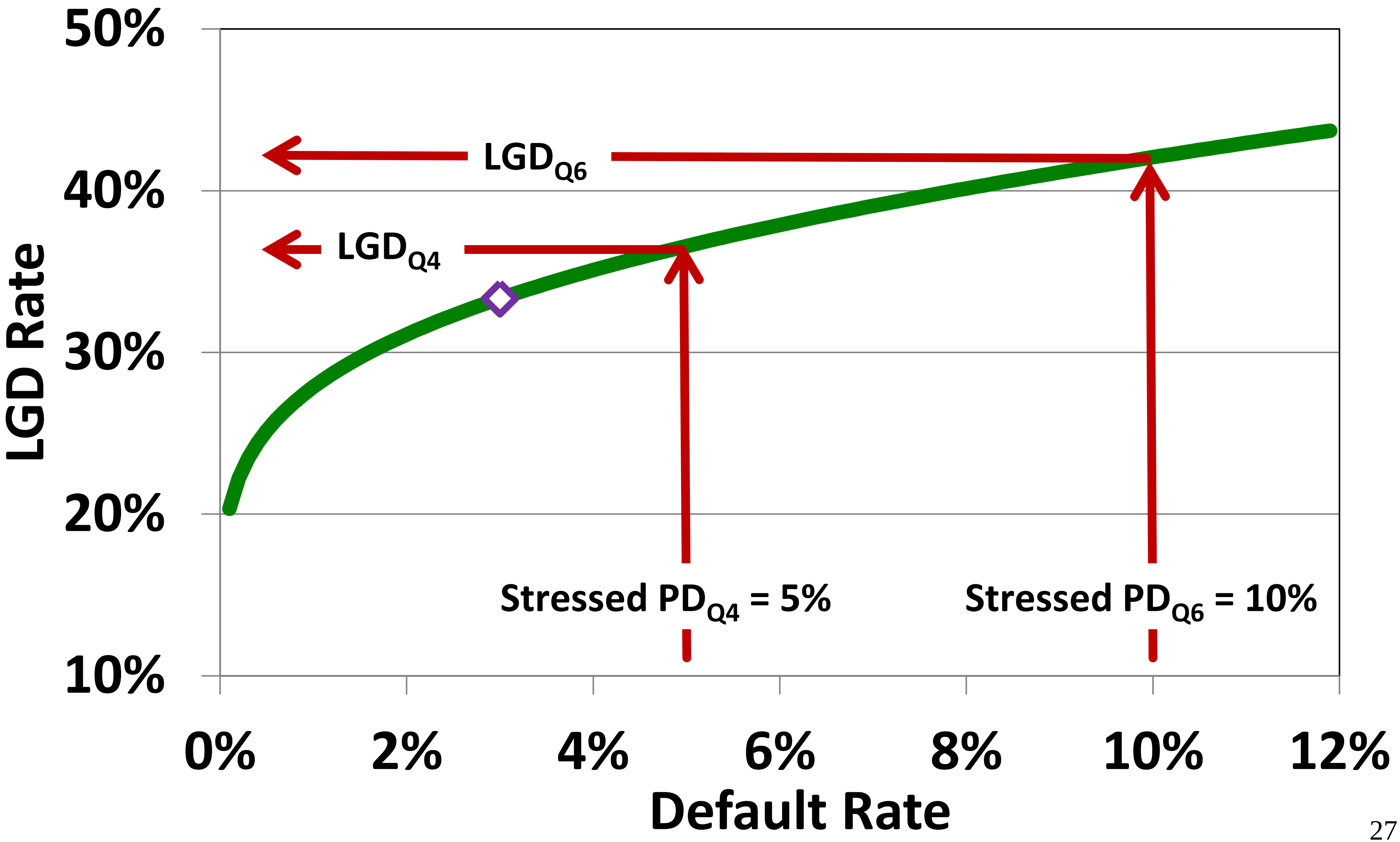
Locate your loan on the chart



Draw the LGD function with $\rho = 0$



Then, stressed PD implies LGD



The Link from Default to LGD

The LGD function is easy to apply,

- **because it introduces no new parameters to estimate.**

It attributes moderate LGD risk to every exposure.

It works well.

- **It is consistent with historical data on loans and bonds.**
- **It outperforms linear regression in simulation experiments.**
- **It is likely to continue to outperform for a long time.**

References

Frye, "LGD as a function of the default rate,"

http://www.chicagofed.org/webpages/people/frye_jon.cfm#

Frye and Jacobs, "Credit loss and systematic loss given default," ***Journal of Credit Risk*** **(1–32) Volume 8/Number 1, Spring 2012.**

Frye, "Modest Means," Risk, January 2010, pages 94-98.

Frye, "Depressing Recoveries," ***Risk*****, November 2000, 108-111.**

Questions?

Thank you for your attention