Comptroller of the Currency
Administrator of National Banks

Assessing the Impact of Changing Economic Conditions on the Design of Default Probability Models

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Agenda

- Motivation
- Data Design
- Alternative Methods
- Results

Motivation

- Recent downturn has been a real challenge for credit-risk modelers
  - Several banks suspended the use of models in 2009
- Default models continued to rank order; however, performed poorly at predicting performance
  - Default rates skyrocketed.

Motivation

- Question:
  - Was the deterioration in model performance due to a 1-in-1000 (i.e., rare) event – an event that could not be predicted and, as a result, impossible to model; or,
  - Are the methods used by banks too simplistic restricting their ability to adopt to changing economic and industry conditions (e.g., static sample design build around credit bureau data)?

Motivation

- Because of two recent changes in the industry:
  - Basel II/IRB requires banks develop reference data sets covering at least a 5 year horizon.
  - Banks have become aware of the importance of changing economic conditions (e.g., unemployment rates, housing prices/current LTV) on defaults.

  banks are beginning to consider alternative model designs.

- Unfortunately, adopting new methods introduces its own set of problems.

Motivation

- Which raises an additional question:
  - Have banks gone too far in the direction of building and implementing more complex models without fully understanding the additional model risks associated with these methods?
    - How will the models be evaluated/validated
    - Is there sufficient data (cross-section/time-series) to allow them to capture the true DGP or are they simply overfitting the new data
      - false correlation may exist over short time horizons
    - How does one determine that the “right” set of economic factors have been identified
      - uncertainty over which systematic factors are correct
      - not all relevant systematic factors are available

Motivation

- The issues:
  - Is it possible to develop models that are less sensitive to large shocks due to rare events; or, will banks continue to be exposed to unforeseen – and unpredictable – shocks that result in model failure?
  - Are current industry practices used to develop risk models contributing to the recent increase in model failure?
  - Will newer (and more complex) modeling approaches significantly improve model performance; or, result in models that perform even worse due to omitted variable and mis-specification?

Motivation

- Focus is on modeling issues related to retail products
  - Large number of observations that allows lenders to rely on the actuarial properties of the portfolios and to develop statistical models for underwrite and account management purposes
  - There are a number of reasonable and valid methods requiring a variety of sample designs outlined in the banking/finance, statistics/econometrics literature.
  - There are strengths and weaknesses associated with each method; knowing their strengths helps us select the best model for the intended purpose, understanding the weaknesses will help avoid falling victim to them.

Motivation

- To address these issues, we need
  - A data set that includes:
    - data over a full business cycle
    - a full set of risk drivers and the corresponding weights
  - A model that represents the true DGP
    - used to evaluate the benefits of alternative methods.
- Unfortunately, a data set that meets all our requirements does not exist.

Motivation

- Limitation of actual data
  - The data generating process (DGP) is unknown.
  - A specific data set will represent a single, yet potentially very complex, DGP driven by factors unknown to the modeler.
  - An actual data set will surely be incomplete missing key factors that define the DGP.

Data Design

- For those reasons, we decided to create our own data set by simulating data that meet the following conditions:
  - Default is based on loan/borrower characteristic (e.g., credit score) and systematic factors (e.g., unemployment rate)
  - Loan/borrower characteristics are correlated (e.g., score and utilization are negatively correlated)
  - Loan/borrower characteristics are correlated with systematic factors (e.g., score is negatively and utilization is positively correlated with the unemployment rate)
  - The characteristics are serially correlated

Data Design

The true PD is governed by:

PD = 1/ (1 + exp(**2.2** + **0.01** score - **1.5** util - **2.5** ur - **0.15** unobs sys factor + **0.125** chg hpi))

*score** - a random variable serially correlated at the individual level, negatively correlated with util, and negative correlated with the monthly unemployment rate (ur)

*util** - a random variable serially correlated at the individual level and positively correlated with ur

ur - the national, seasonally adjusted monthly unemployment rate, 1992.01 through 2010.12

unobs systematic factor - an independently drawn random variable correlated with ur only by chance

chg hpi - the 3-month average change in the monthly House Price Index (new purchases only).

*score and utilization are "labels" assigned to the random variables we create; they are not related or calibrated to actual credit scores or utilization data.

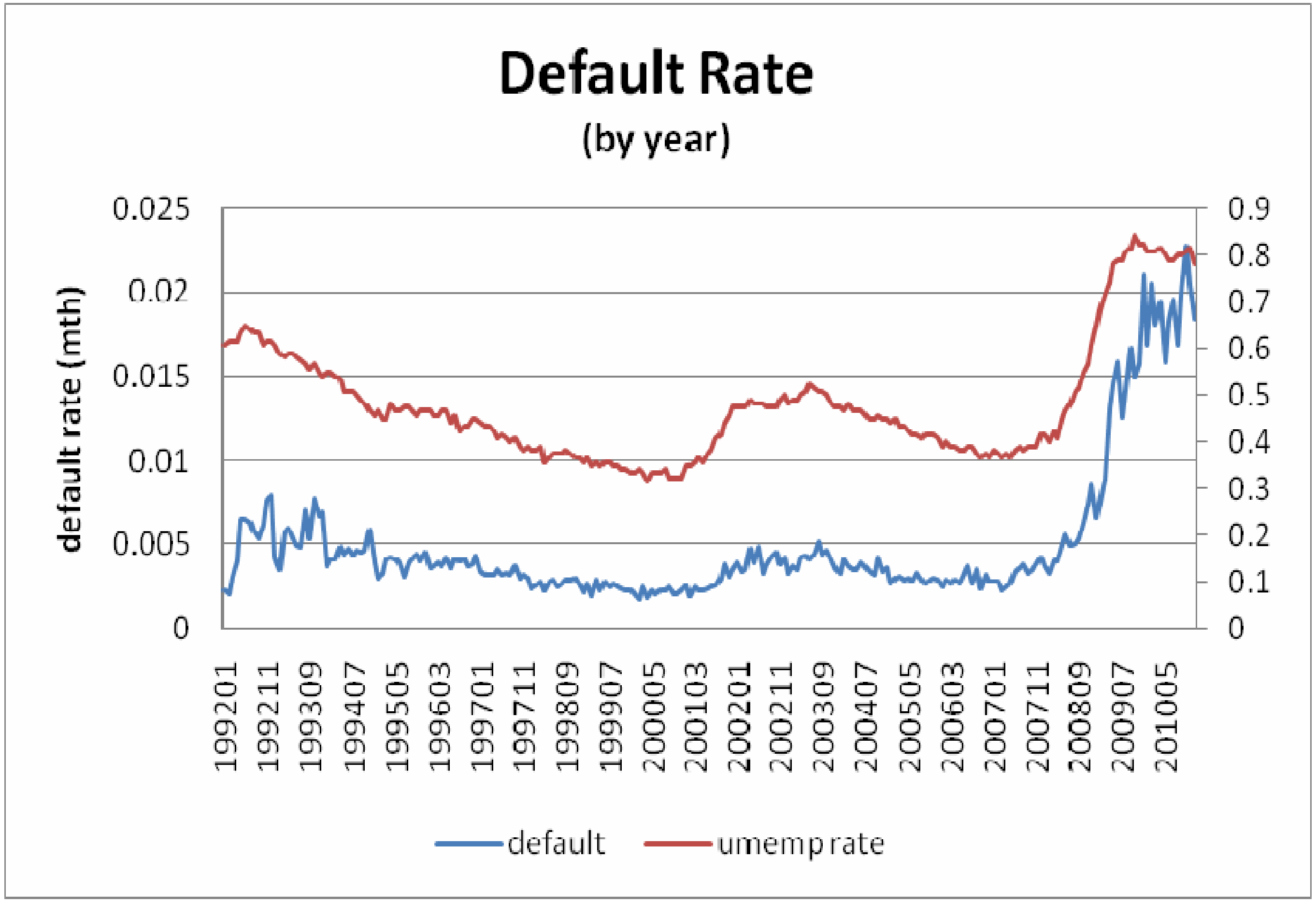
Data Design

- Additional conditions imposed:
  - We mimic the underwriting process by assuming that lenders book accounts only in the upper end of PD distribution (lower PD segments): true PD less than 0.1.
  - Default is stochastic process with the probability of default equal to PD (i.e., if 1000 exposures have PDs equal to .05, on average 50 will be randomly assigned to the default state).
  - Prepayment probability:

$$PP = 1/\left(1 + \exp\left(\mathbf{9.5} - \mathbf{0.005}\ \text{score} + \mathbf{0.75}\ \text{change mtg rate} + \mathbf{0.015}\ \text{unobs sys factor} - \mathbf{1.25}\ \text{chg hpi}\right)\right)$$

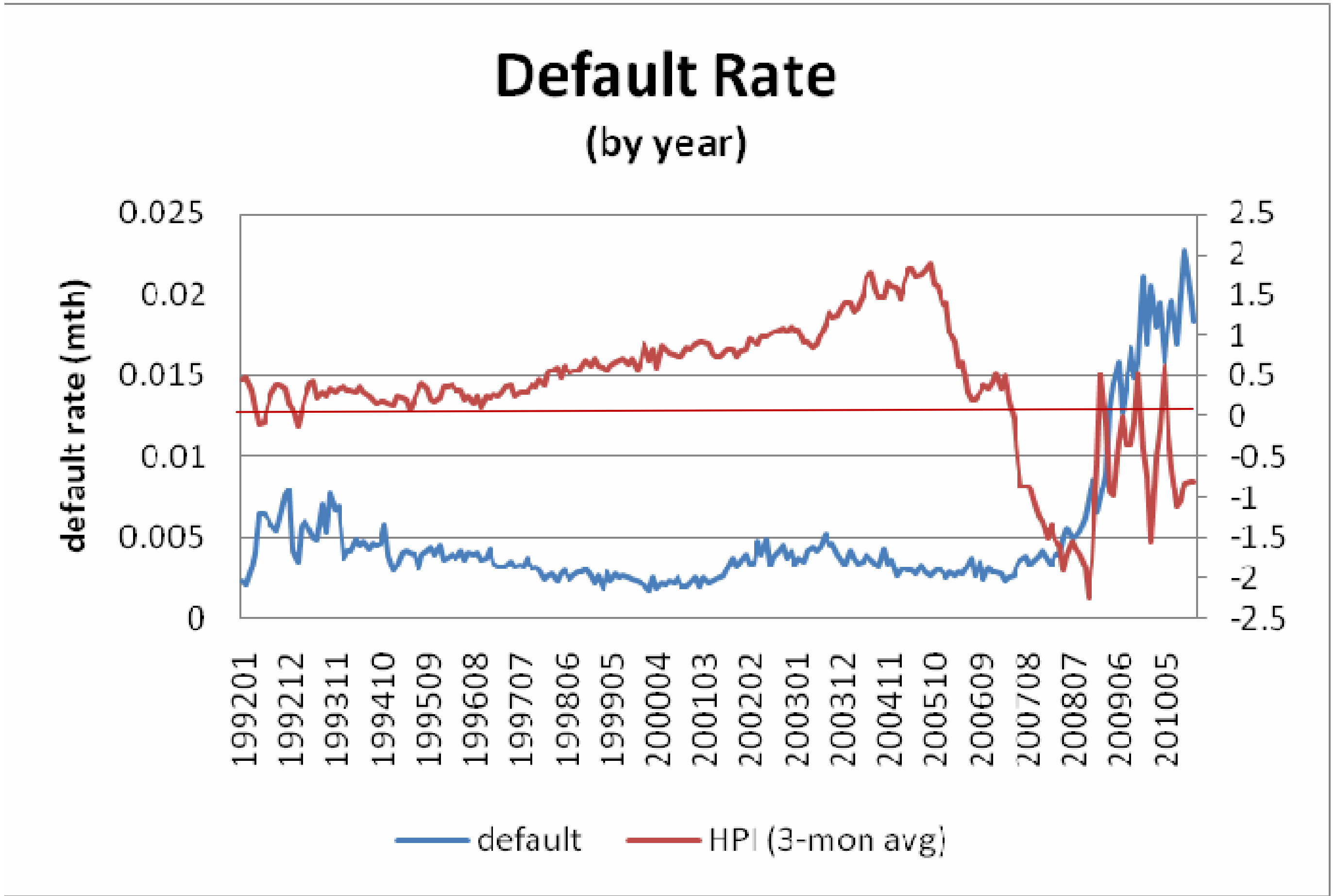
  - Three new origination pools (i.e., vintages) were drawn each year (total: 57 vintages) each with a 60-month term.

Data Design



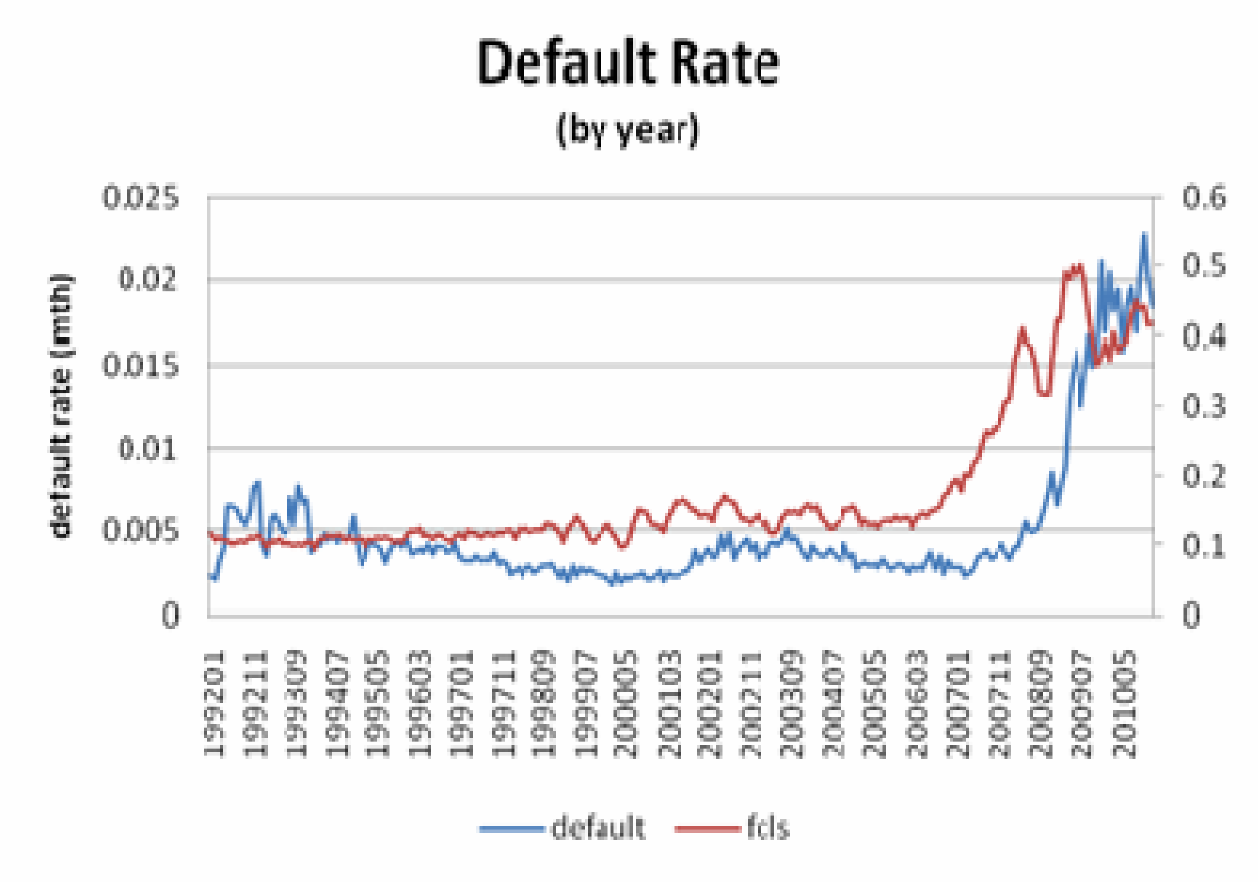
Default Rate
(by year)
default rate (mth)
0.025
0.02
0.015
0.01
0.005
0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
199201
199211
199309
199407
199505
199603
199701
199711
199809
199907
200005
200103
200201
200211
200309
200407
200505
200603
200701
200711
200809
200907
201005
default
umemp rate

Data Design



Default Rate
(by year)
default rate (mth)
0.025
0.02
0.015
0.01
0.005
0
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
199201
199212
199311
199410
199509
199608
199707
199806
199905
200004
200103
200202
200301
200312
200411
200510
200609
200708
200807
200906
201005
default
HPI (3-mon avg)

Data Design



Default Rate
(by year)
default rate (mth)
0.025
0.02
0.015
0.01
0.005
0
0.6
0.5
0.4
0.3
0.2
0.1
0
199201
199211
199309
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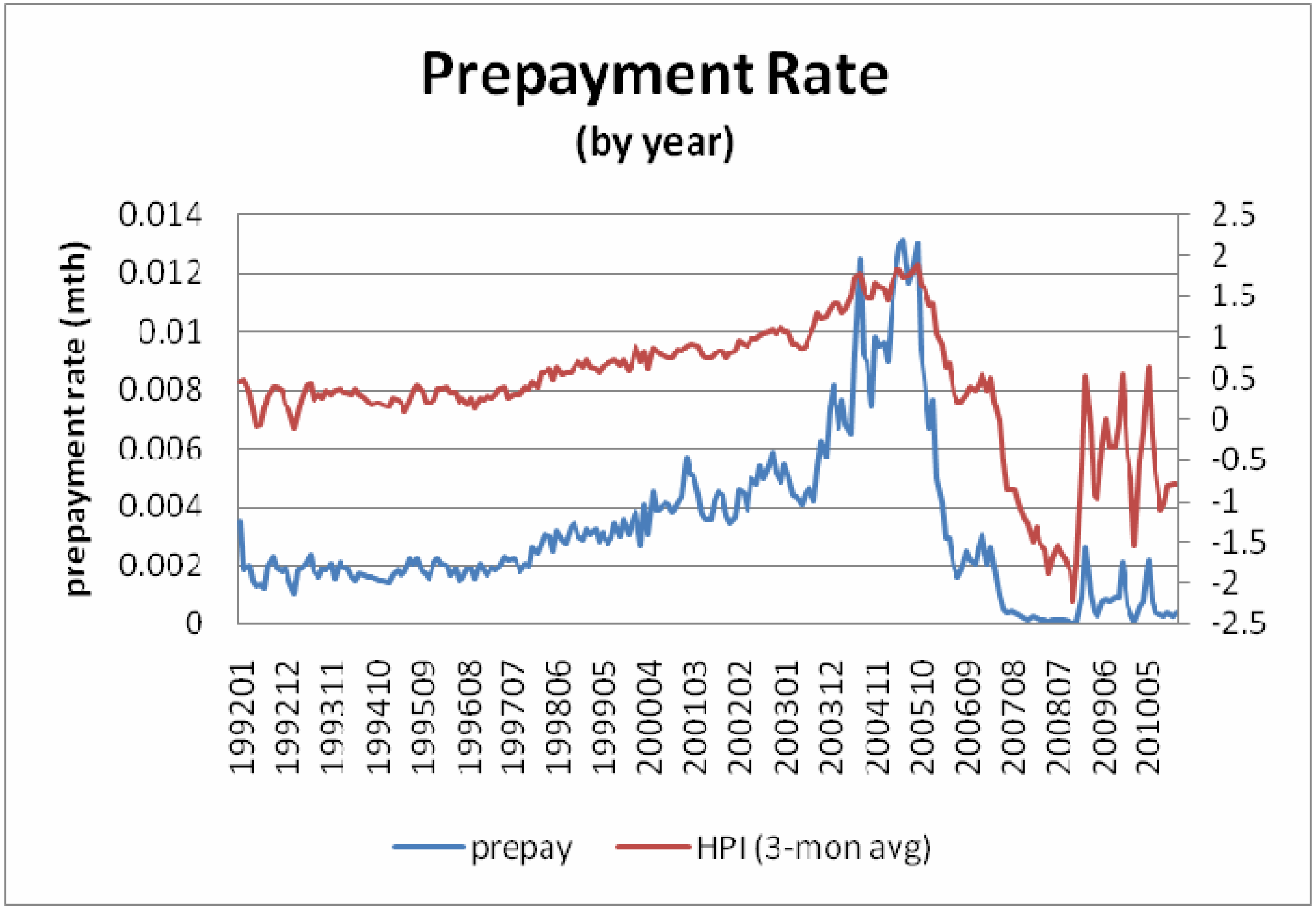
default
fcls

Data Design



Prepayment Rate
(by year)
prepayment rate (mth)
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
199201
199212
199311
199410
199509
199608
199707
199806
199905
200004
200103
200202
200301
200312
200411
200510
200609
200708
200807
200906
201005
prepay
HPI (3-mon avg)

Alternative Methods

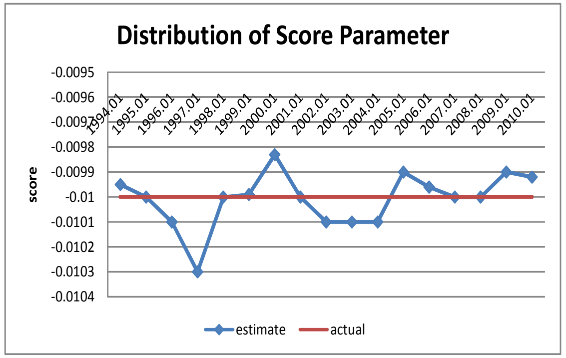
- Full data set (monthly predictions)
- Partial data set: estimate model using five-years of data
  - Monthly predictions
  - Annual cohort predictions

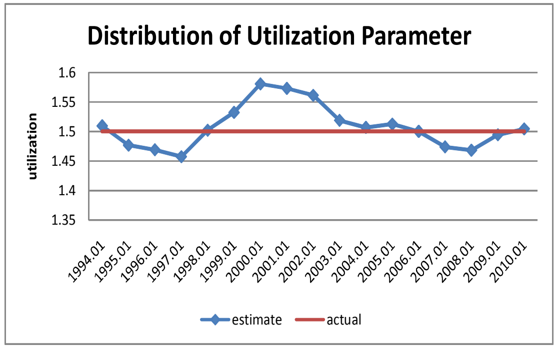
Results

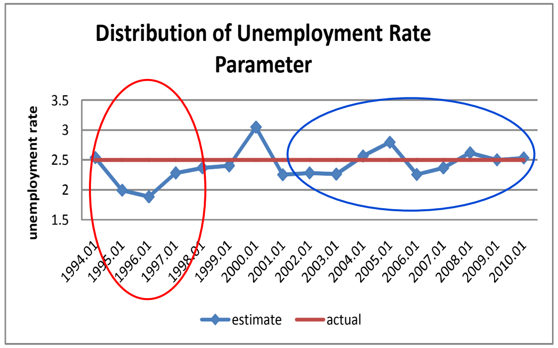
Table 1. Estimated Model: 1992.01 - 2008.12

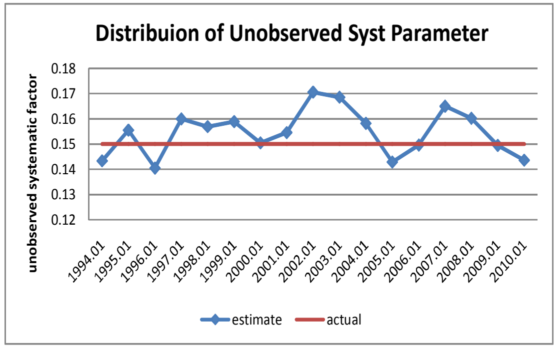
Variable	*B*	*std err*	*p-value*
Intercept	-2.21	0.041	0.0001
SCORE	-0.01	0.000055	0.0001
UTIL	1.5119	0.0132	0.0001
UR	2.5041	0.0469	0.0001
UNOBS_Y	0.1545	0.00355	0.0001
C_HPI	-0.1249	0.0038	0.0001
H-L Stat	0.7335		
	In sample	Out-of-sample	
		1-year (2009)	2-year (2010)
non-default	24,145,592	1,504,352	949,379
Default	85305	23,281	18,298
actual default rate	0.352%	1.524%	1.891%
est default rate	0.352%	1.537%	1.891%
RMSE	0.0030%	0.0137%	0.0147%

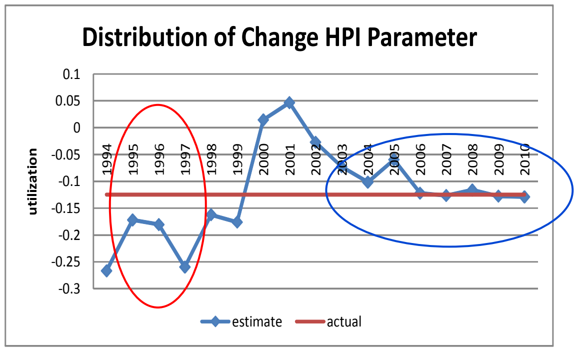
Results









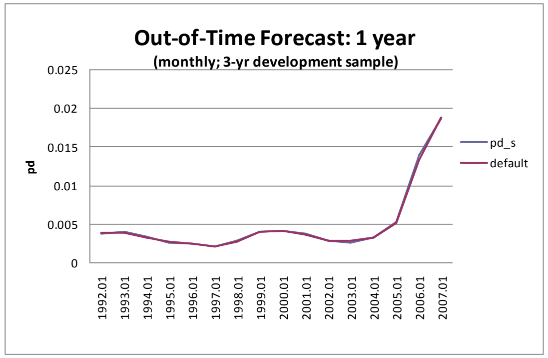


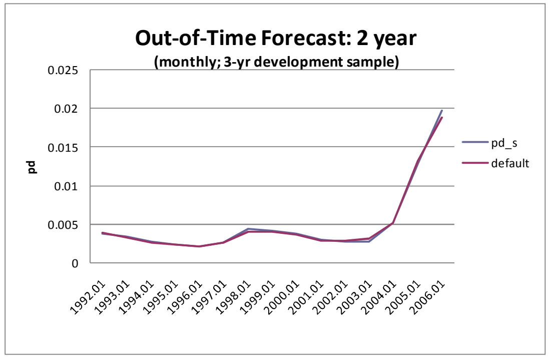
Estimated parameters are sensitive to changing economic conditions.

Variation in the systematic factors is critical for purposes of model identification.

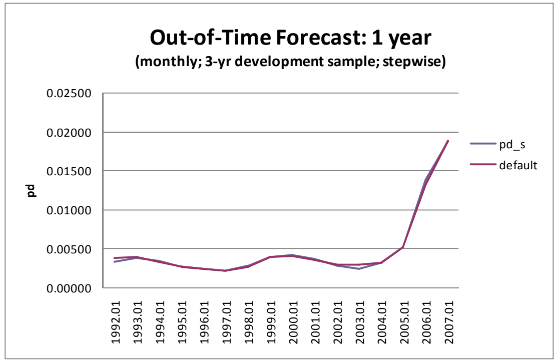
Results

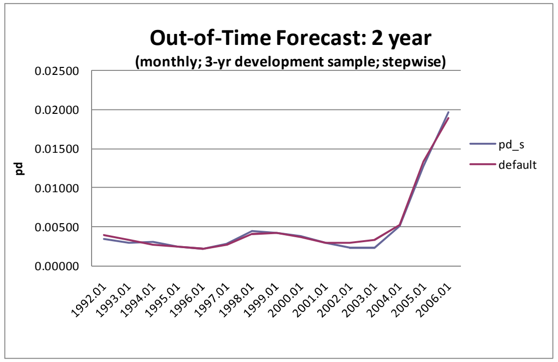
- Exact Specification (score, util, ur, unobs sys factor, c_hpi)



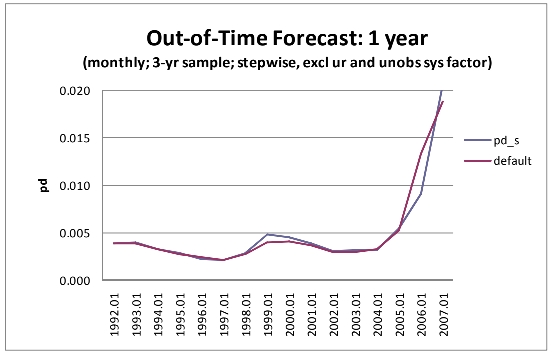


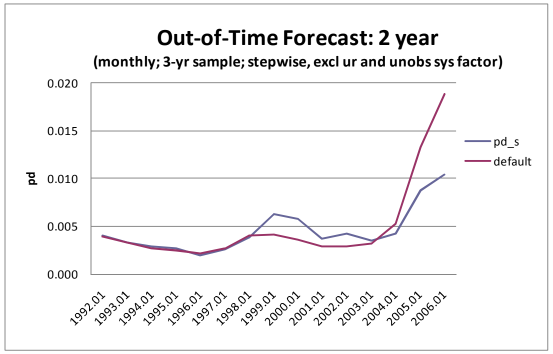
- Stepwise Specification (complete set of systematic risk factors)





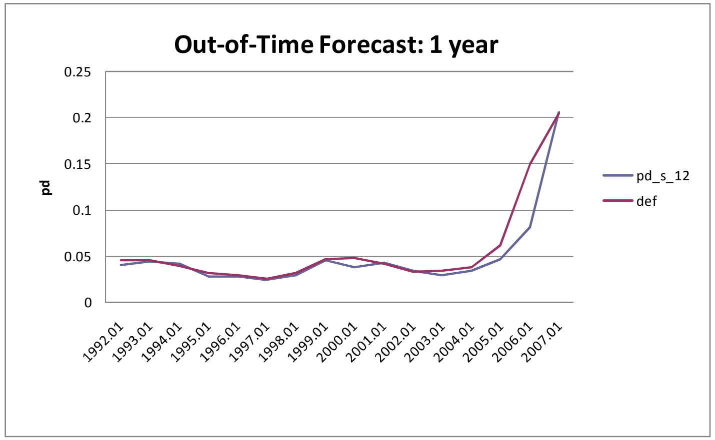
- Stepwise Specification (exclude ur and unobs sys factor from list of risk factors)





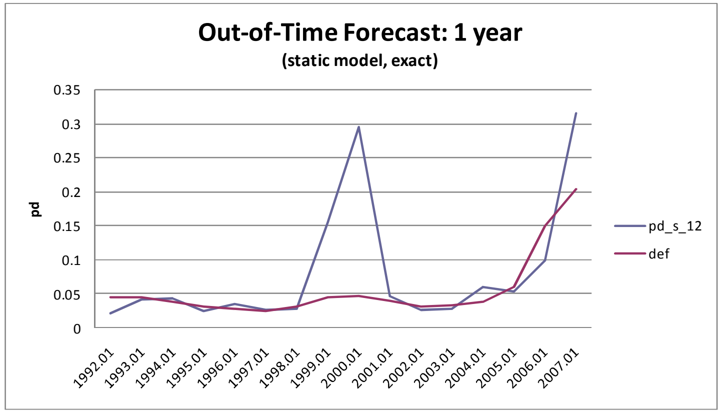
Results

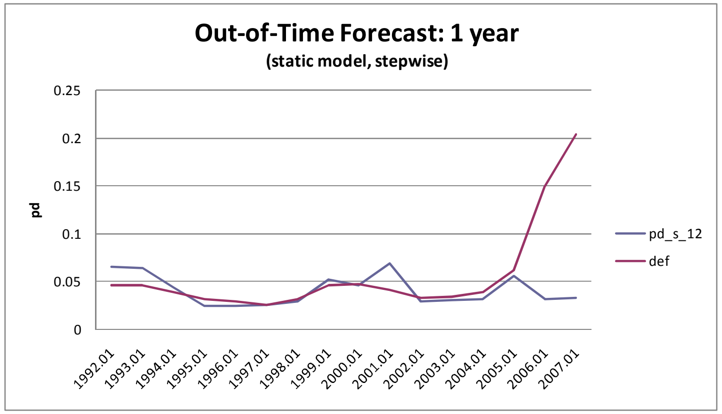
- Are the results from the complex model that much better than those from a static model?



- Monthly default rates converted to annual rates
- 12-month performance horizon for static model

- A static model design performs poorly during changing economic conditions.





Discussion

- Adopting a dynamic sample design comes with its own sources of model risk.
  - *Excluding relevant systematic factors* correlated with included factors will likely bias the estimate of the parameters of the included variables.
  - Even in cases where the true parameters are contained in the confidence interval around the estimated parameters, the quality of out-of-sample predictions are adversely impacted by *imprecisely estimated coefficients* associated with systematic factors
    - as a result, it is possible that the inclusion of systematic factors does more harm than good in terms of out-of-sample performance.

Alternative Approach

- Almost surely one or more key variables will not be available.
- As a result, models will surely fail during periods when the unobserved or omitted variables are more unstable.
  - This is likely to be of greater concern when the reference period is limited to only a few years of data.

Alternative Approach

- We propose the following alternative method:
  - The model

$$PD_{it} = \frac{1}{1 + \exp\{ \;\; \beta' x_{it} \quad \gamma' z_t \quad \varepsilon_t \}}$$

where

x_{it}	loan specific factors (score, utilization)
z_t	observable systematic factors (ur, change HPI)
ε_t	unobserved systematic factor; assume $N(0,\sigma)$

Alternative Approach

- Because of the unobservable factor we cannot directly identify all model parameters.
- However, if we estimate:

$$PD_{it} = \frac{1}{1 + \exp\{-\beta' x_{it} - \delta_t\}}$$

where

δ_t calendar-time fixed effects

then estimates of the parameters γ and σ can be estimated from the OLS regression of

$$\hat{\delta}_t = \gamma' z_t + \varepsilon_t$$

Alternative Approach

- Advantages of this approach:
  - Including calendar time fixed effects in the first step ensures that the model captures the impact of all observed and unobserved systematic factors without having to assume they are uncorrelated with the included variables that vary also across individuals.
    - eliminate the possibility that the coefficients on the included variables are contaminated as a result of being correlated with relevant but omitted or unobserved systematic factors.

Alternative Approach

- Advantages of this approach (cont):
  - Allows for more flexibility in designing out-of-sample forecasts.
    - from the decomposition, an estimate of the distribution of the unobservable systematic factors can be derived.
    - VaR-like default rate predictions at different percentiles in the distribution of unobservable systematic factor also can be easily derived, as long as we are willing to make a distributional assumption
      - note: the distributional assumption can be tested empirically

Alternative Approach: Results

Table 2: Regression results

VARIABLES	(1)	(2)	(3)	(4)
Score	-0.00983***	-0.0123***	-0.00979***	-0.00983***
	(0.000153)	(0.000147)	(0.000153)	(0.000154)
Util	1.526***	1.404***	1.527***	1.526***
	(0.0362)	(0.0361)	(0.0362)	(0.0363)
Ur	2.577***		2.537***	2.519***
	(0.0605)		(0.0604)	(0.0953)
c_hpi	-0.114***		-0.117***	-0.123***
	(0.0102)		(0.0101)	(0.0139)
unobs_y	0.164***			0.1513***
	(0.0162)			(0.0162)
Constant	-2.302***	-2.379***	-1.262***	-2.321***
	(0.198)	(0.197)	(0.144)	(0.051)

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

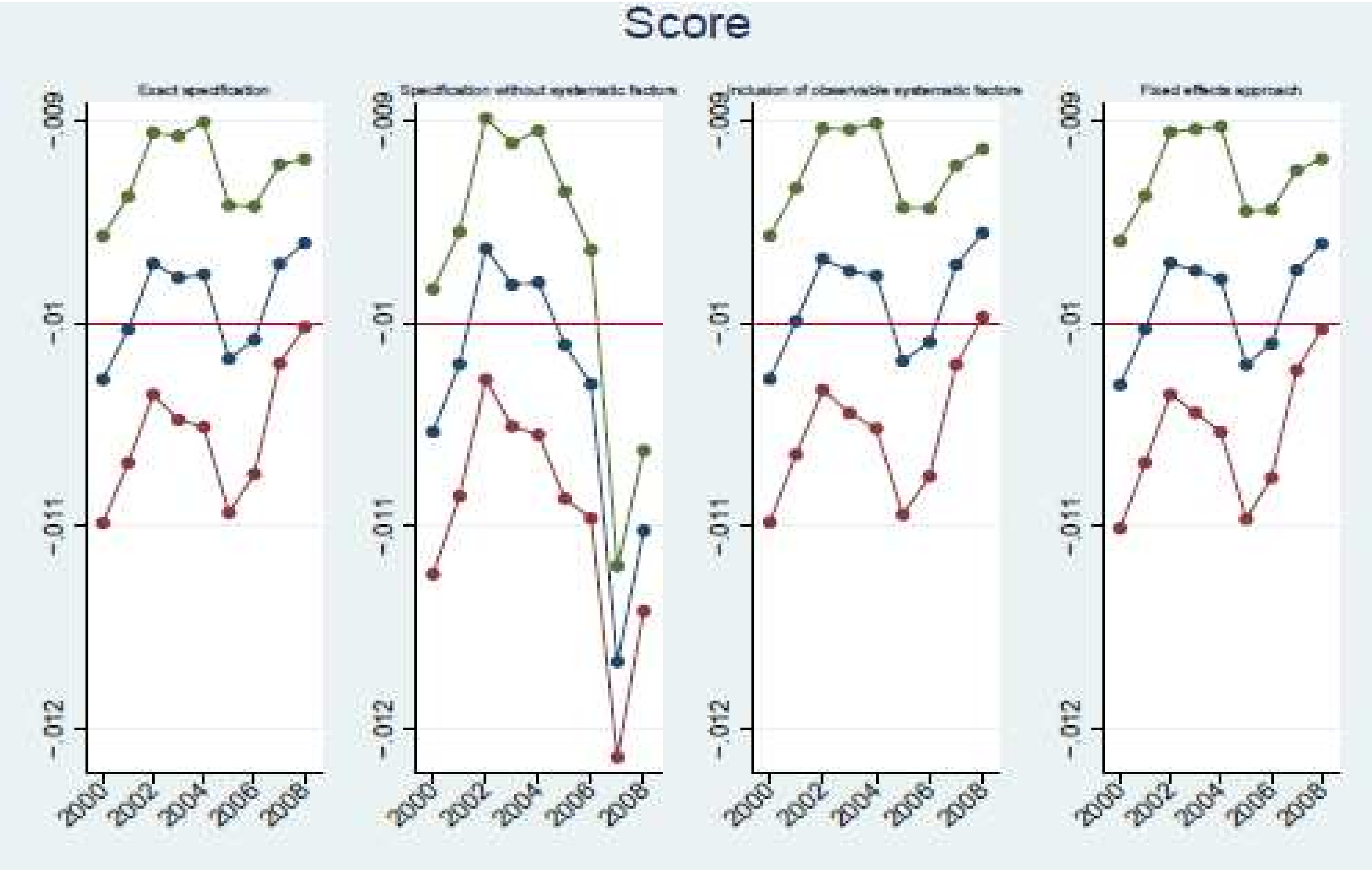
Alternative Approach

- The results in the previous table are presented as a benchmark based on a 5% sample of the full data set (19 years of data).
- We are, however, more interested in how well the alternative approach performs when the development sample covers a relatively short time horizon.
- The results in the following figures are based on models developed using three-years of monthly data.

Alternative Approach: Results

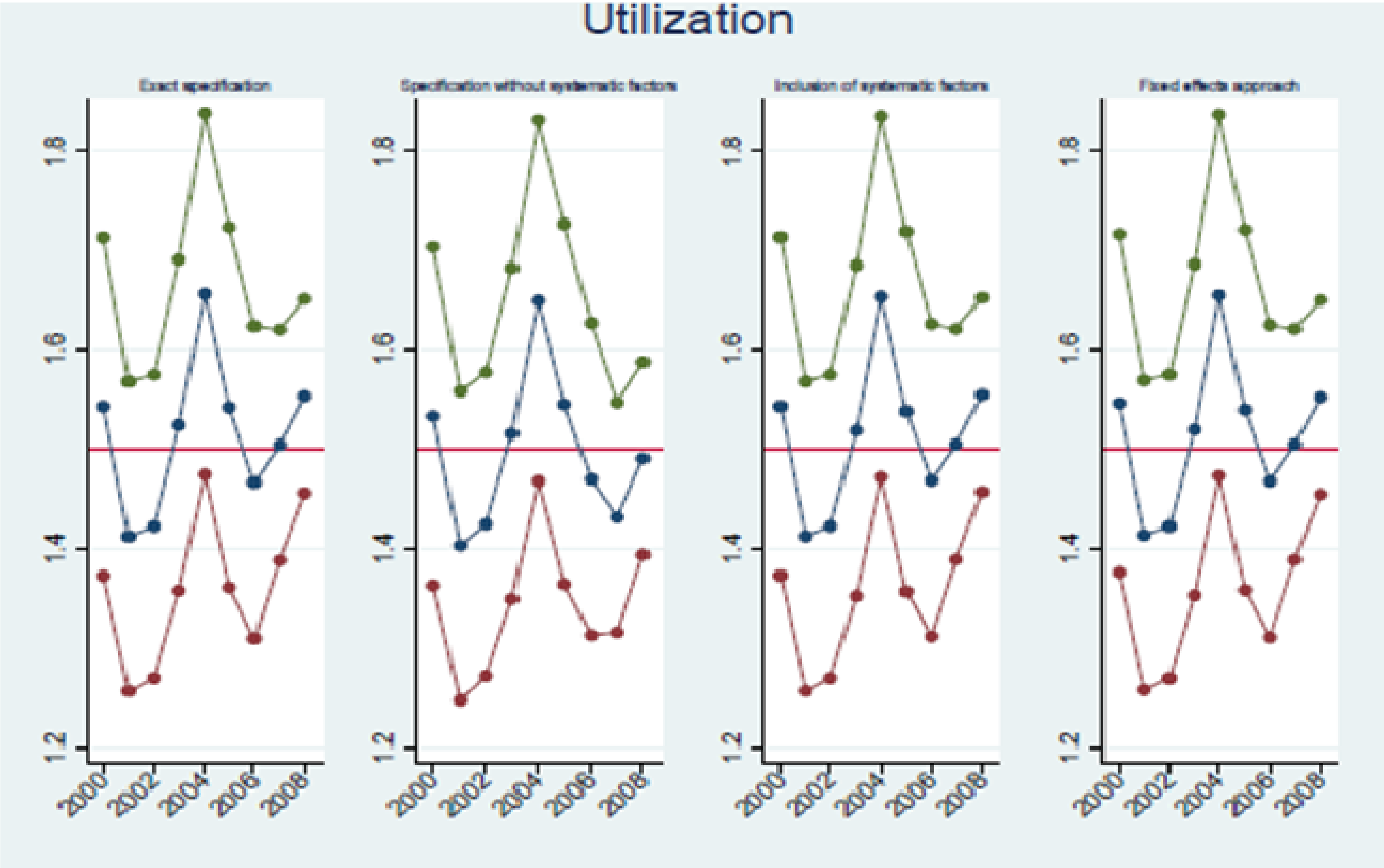
- We graph the point estimates and 95% confidence interval bands for each of the parameters in the following figures.
- The graphs show that the estimated parameters vary across samples.
- We also show that the in some cases the true parameter falls outside the confidence bands.

Alternative Approach: Results



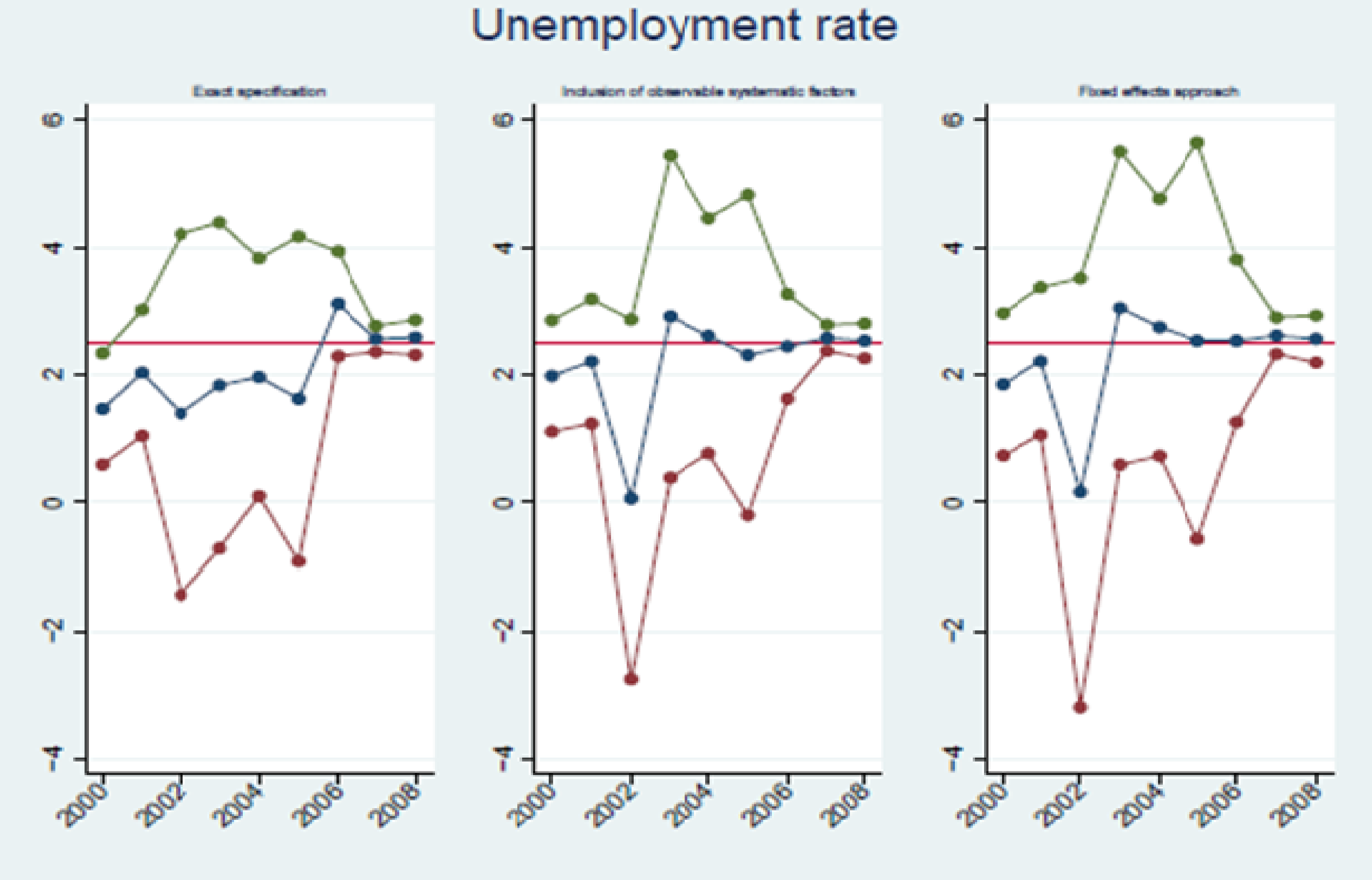
exact specification excl systematic factors incl obs sys factors fixed effect

Alternative Approach: Results



exact specification | excl systematic factors | incl obs sys factors | fixed effect

Alternative Approach: Results

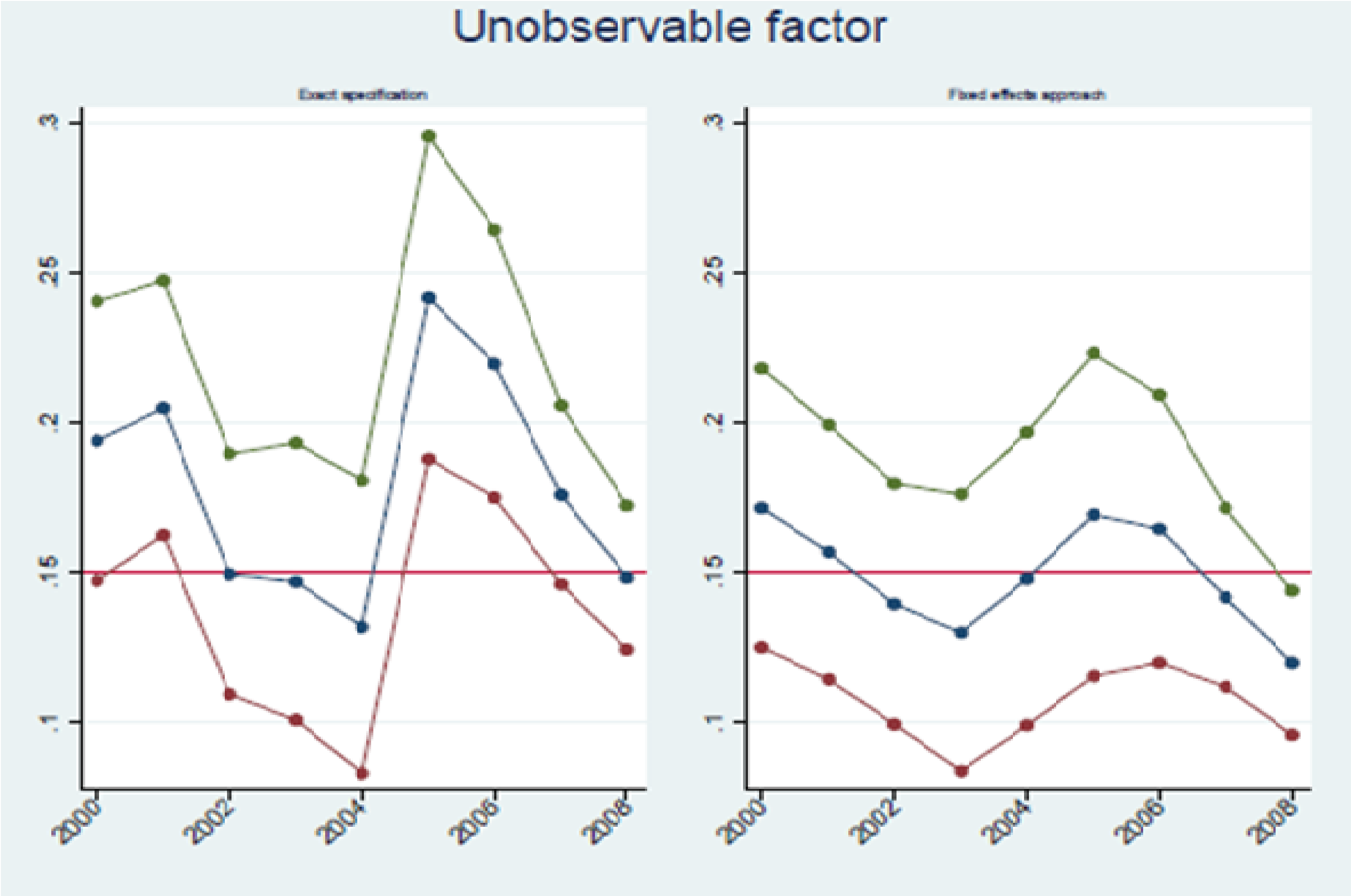


exact specification | include observed sys factors | fixed effect

Alternative Approach: Results

exact specification | include observed sys factors | fixed effect

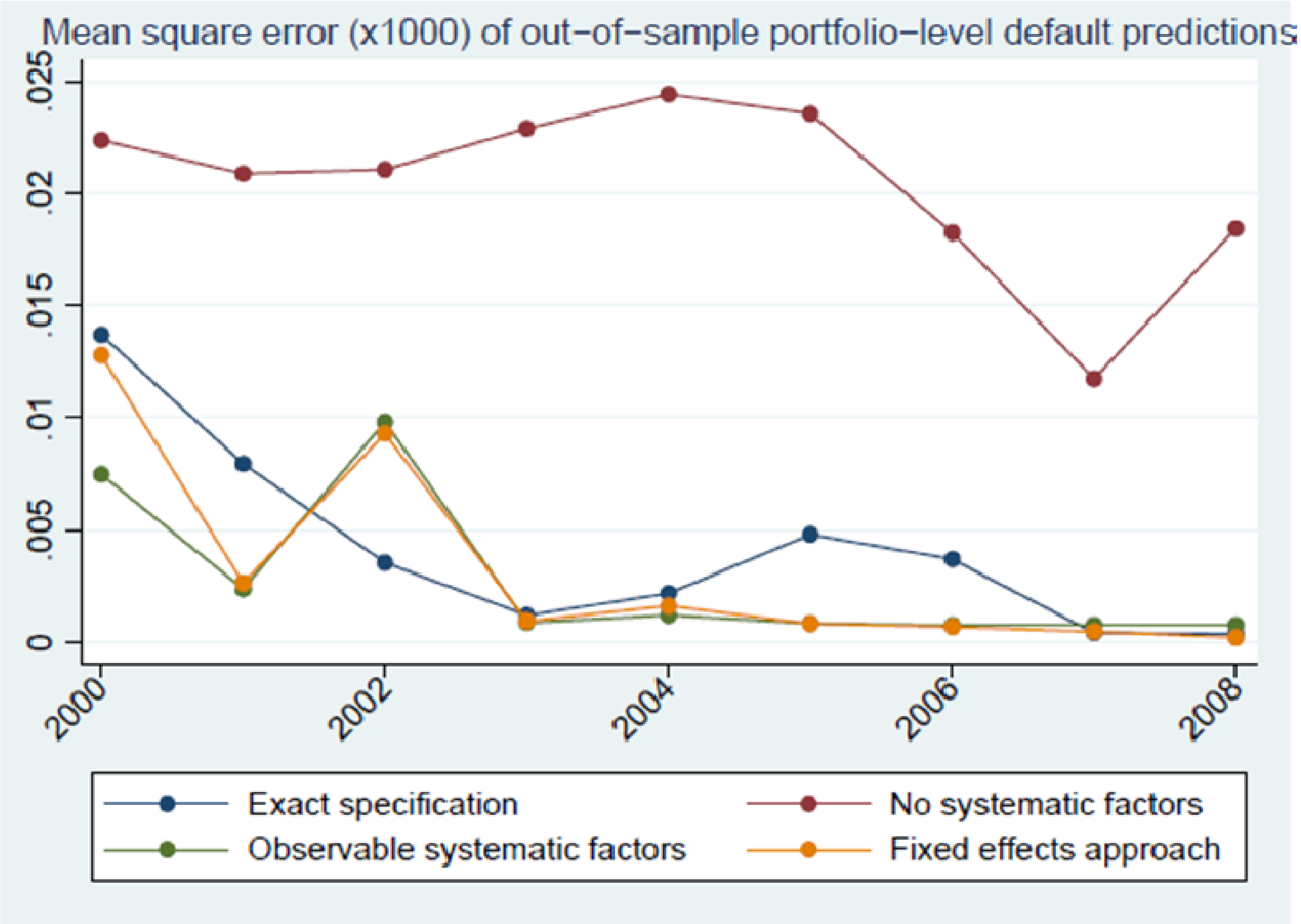
Alternative Approach: Results



exact specification

fixed effect

Alternative Approach: Results



Extensions

- Introduce a more complex simulated sample design
  - Seasoning (aging of the portfolio)
  - More complex correlation structure
  - Nonlinear interactions
- Stress the parameters to replicate a severe downturn
- Evaluate alternative methods under extreme shocks
  - Nonparametric methods

Conclusion

- In response to the increase in model failure during the recent downturn, banks are redeveloping their models using methods that explicitly capture the effects of time varying economic/market conditions.

  - As a result, the models (if correctly specified) are more likely to predict defaults during periods of rapid changes in the market.

Conclusion

- The newer methods, however, are more complex and therefore more likely to increase model risk, especially if
  - the development data does not include the full set of risk drivers (i.e., omitted variables)
  - the development sample spans a relatively short time horizon (i.e., spurious correlation)

- We propose a simple and potentially powerful approach for capturing the effects of unobserved systematic factors:
  - a fixed effects approach