

# CREDIT SCORING & CREDIT CONTROL XIII

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# The Influence of Financial Crisis on UK SMEs Behaviour

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# content

- Background
- Build panel models
  - Use of weight of evidence
  - Reduce independent variables
  - Select panel for four years
- Fixed effect or random effect
  - Failure of Fixed effect
- Influence from macro variables
  - One at a time
  - Set of best AIC

# Background

- SMEs credit scoring: 4.9m SMEs in UK(BIS,2009), 2.3m covered by our data.
  - The ‘Credit Crunch’ :
    - aggregately default
    - public and supervisors’ concern
  - Basel III: consistent internal rating system
- Lack of research in SMEs’ behaviour:  
Challenge: missing category, performance variation between with not clear pattern, large data short time period
- Constant model during economic downside

# Contributions

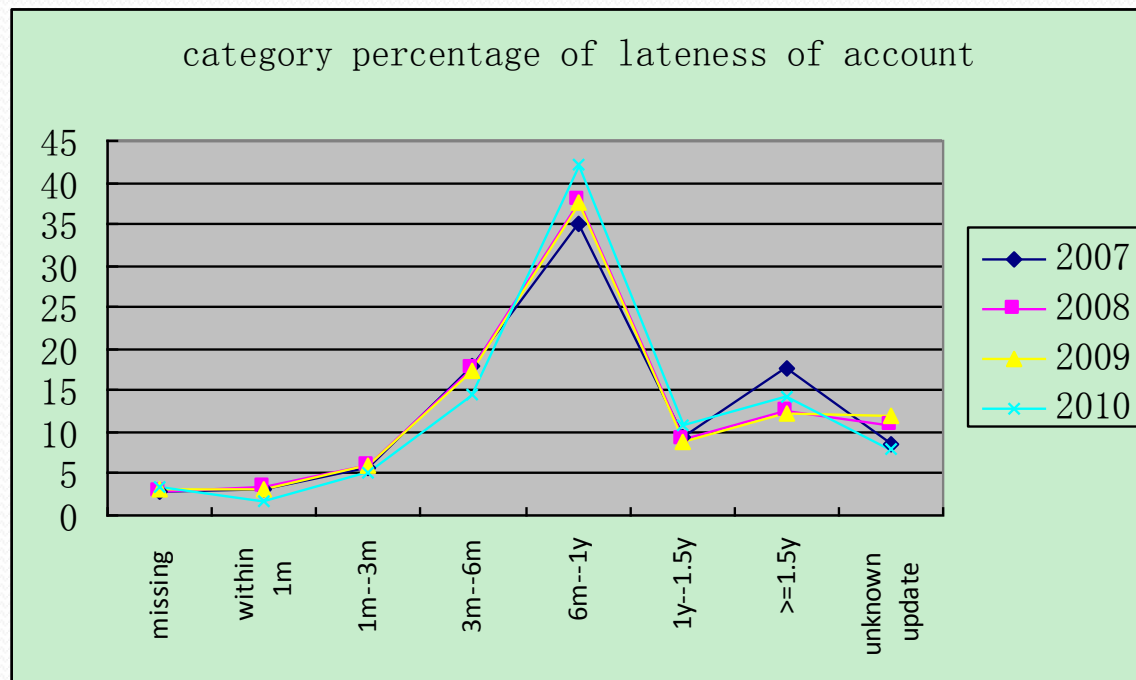
- Analysis of SMEs during ‘credit crunch’
- Multi-time-level modelling of SMEs default probability: using panel data for credit scoring
- Obtaining macroeconomic variables into SMEs modelling

# Training sample

- Selected Training sample
  - Start-ups: younger than 36m
  - Non-start-ups: older than 36m

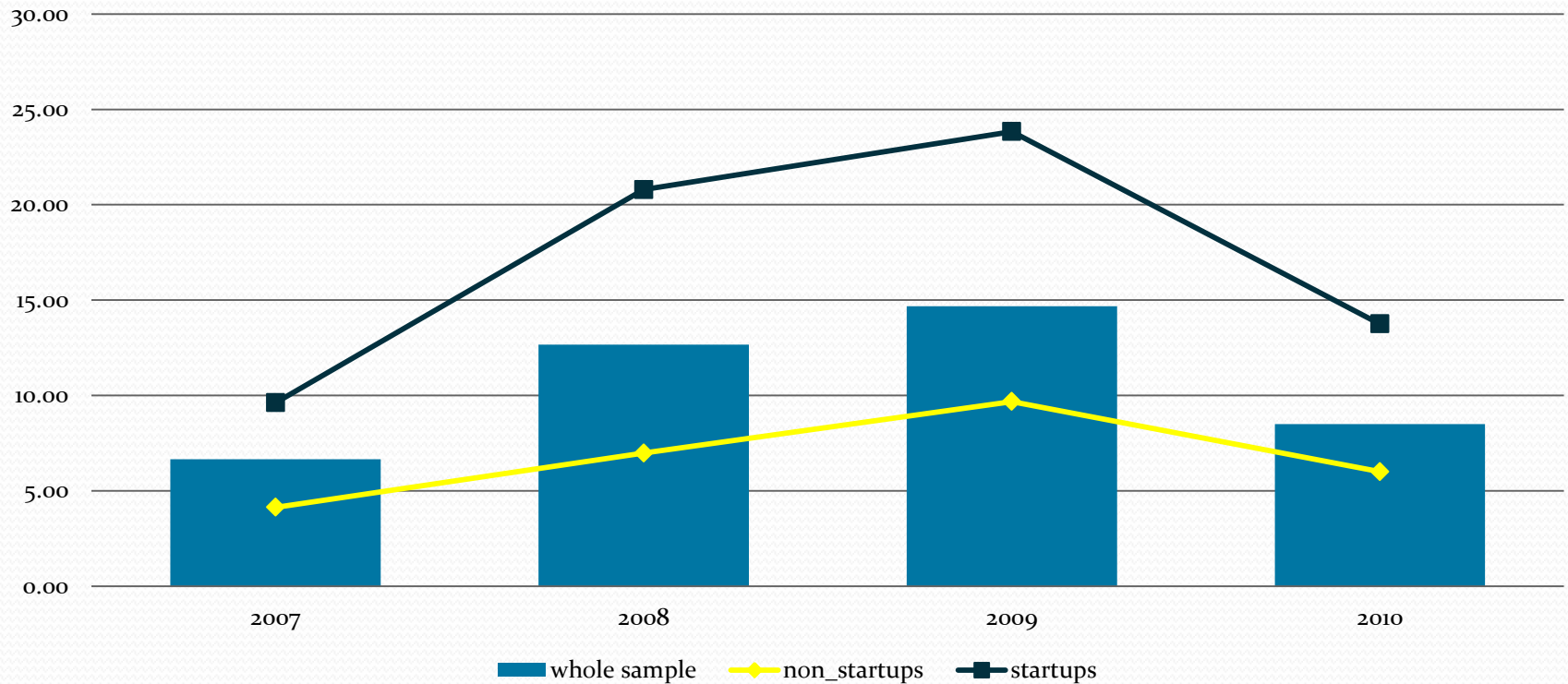
Size of the training sample				
year	2007	2008	2009	2010
Non-start-ups	111,021	103,072	94,039	83,697
Start-ups	94,742	72,034	51,350	39,773
total	205,763	175,106	145,389	123,470

# Lateness of Account



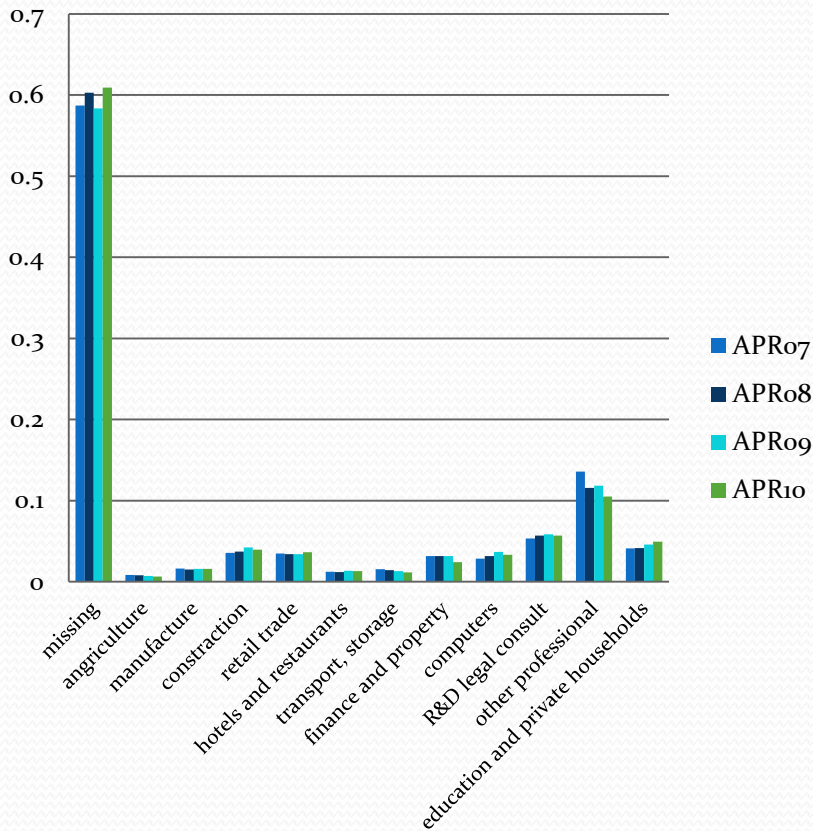
# SMEs Performances

UK SMEs 'bad' rate during the 'credit crunch'

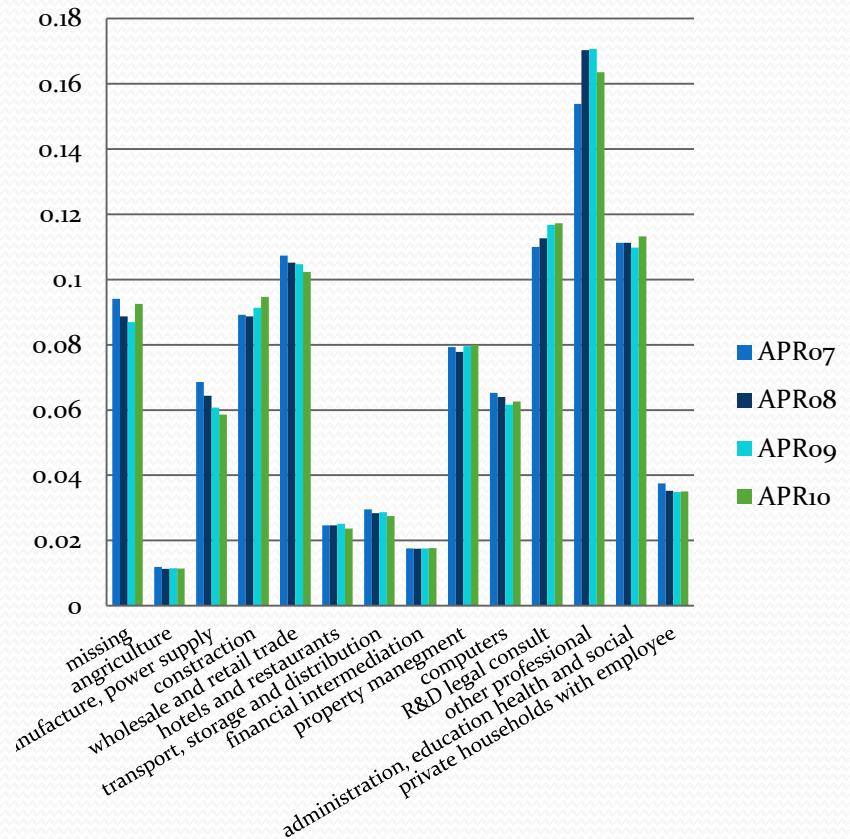


# SME's Categorical Performances

Start-up SMEs %: 1992 SIC Code

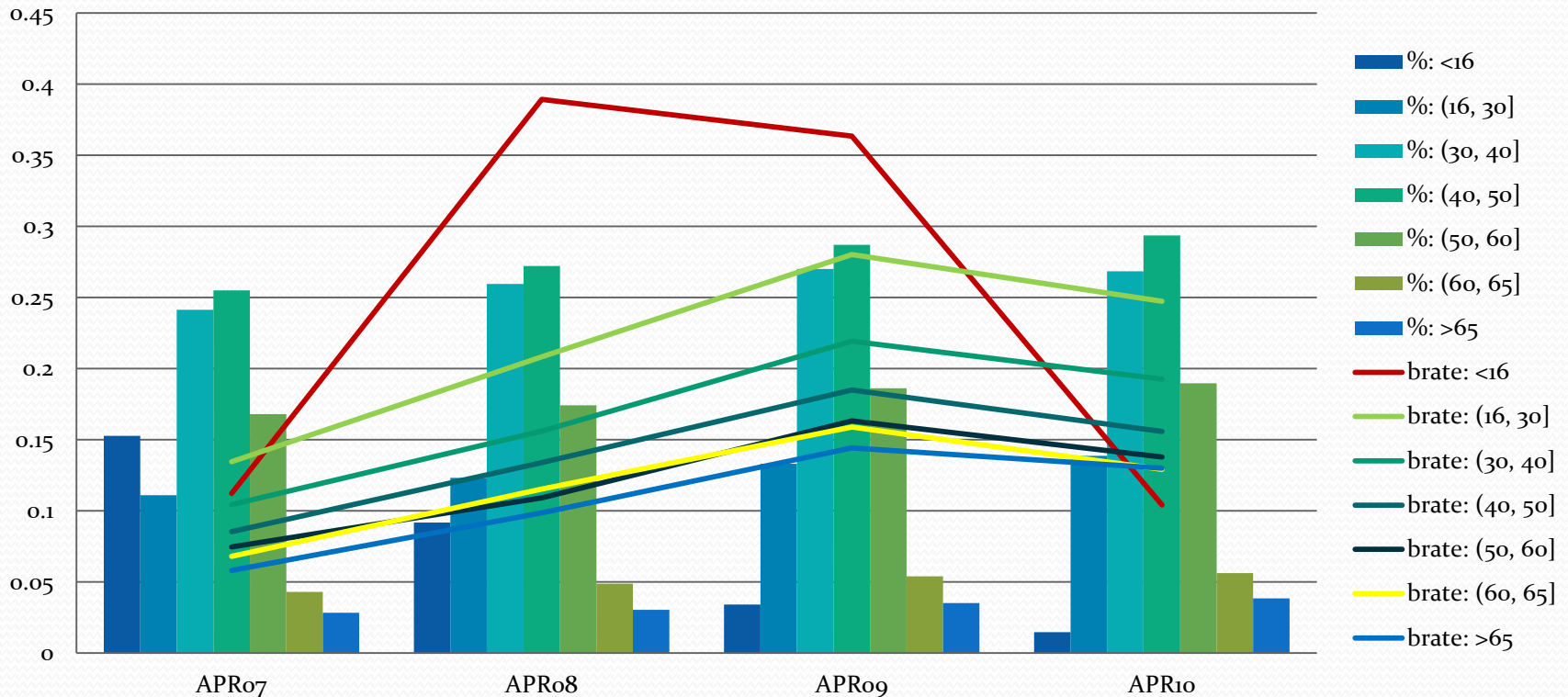


Non-Start-up SMEs %: 1992 SIC Code



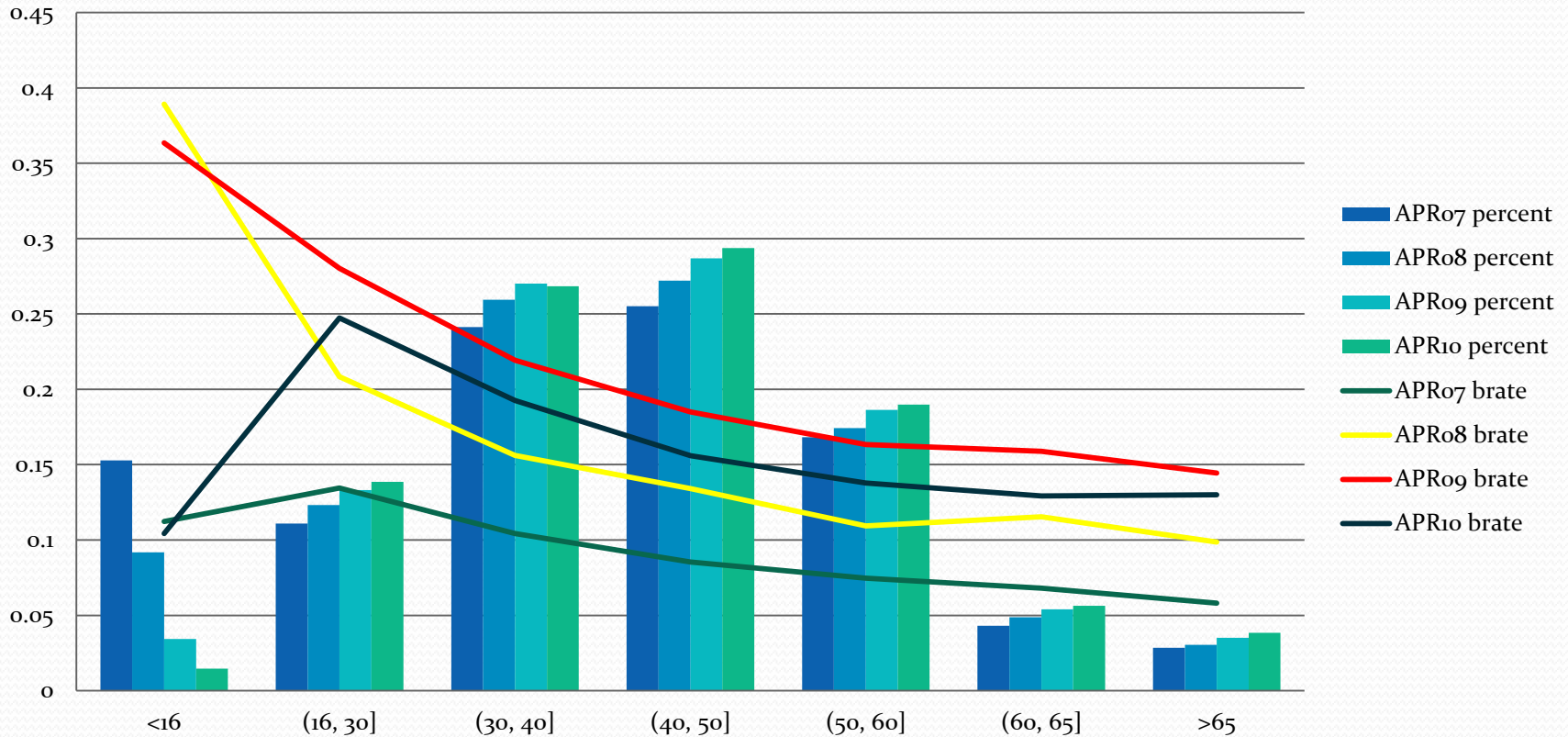
# SME's Categorical Performances

## Start-up SMEs Statistics: Oldest Age of Current Directors



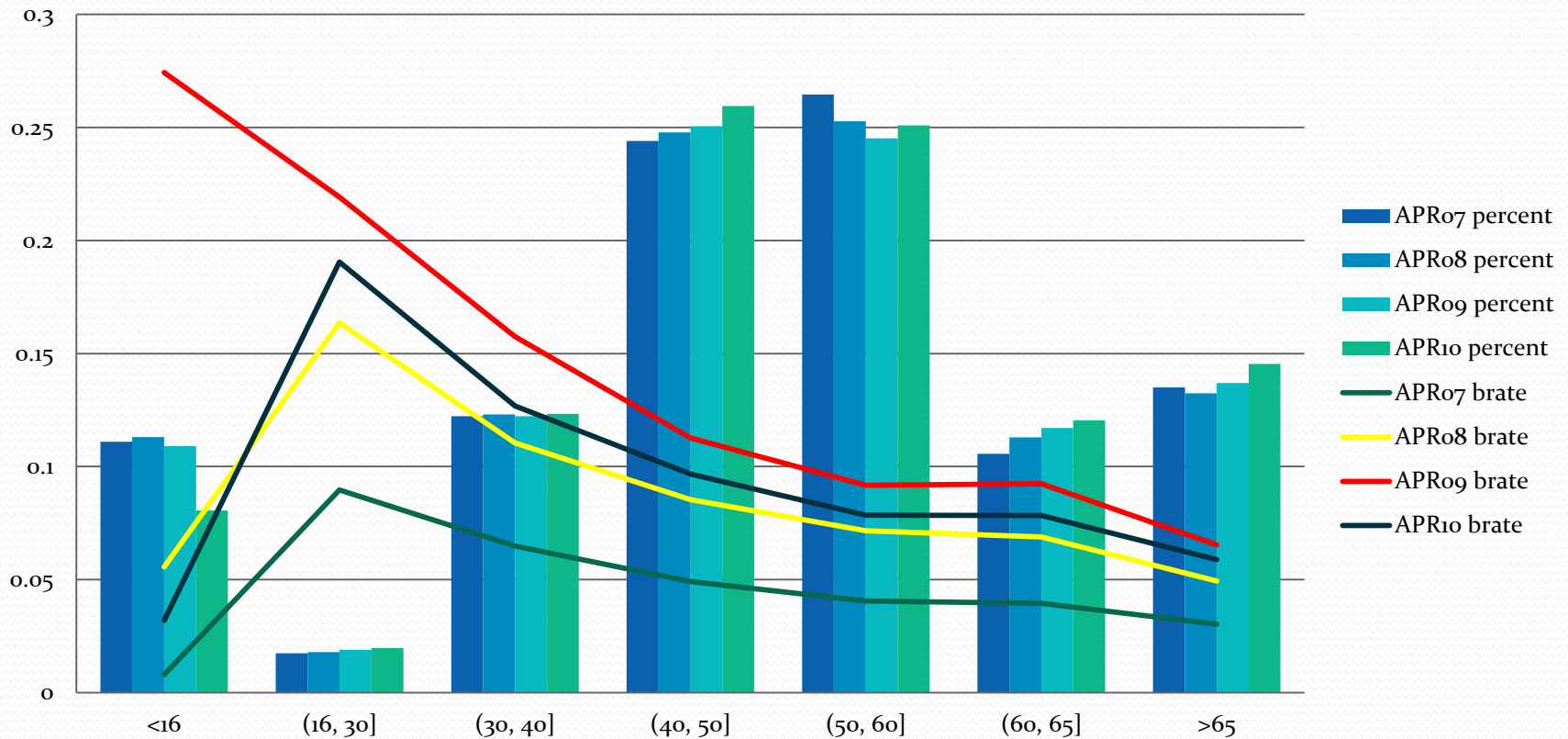
# SME's Categorical Performances

**Start-up SMEs Statistics:  
Oldest Age of Current Directors**



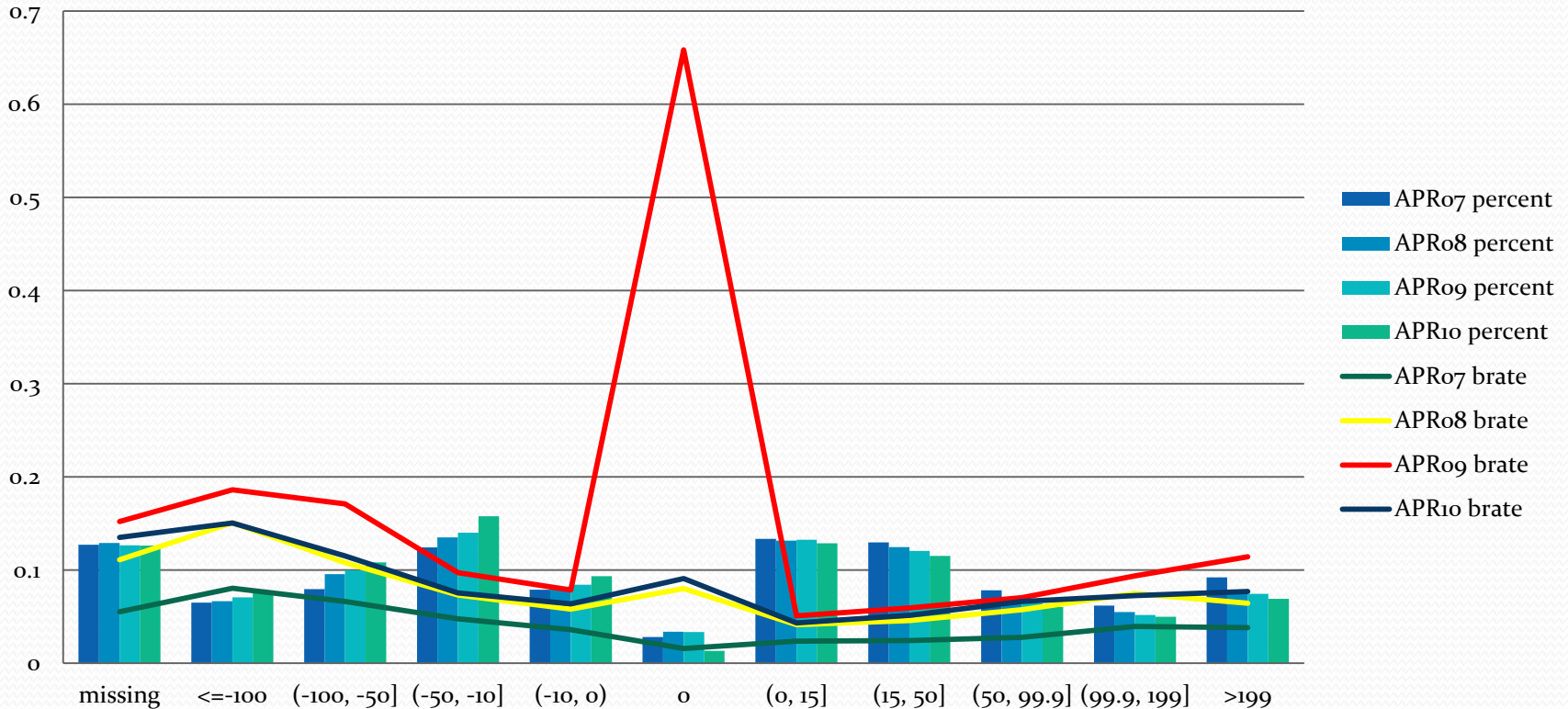
# SME's Categorical Performances

**Non-Start-up SMEs Statistics:  
Oldest Age of Current Directors**



# SME's Categorical Performances

**Non-Start-up SMEs Statistics:  
% Change in Shareholders Funds**



# Use of WoE

- Weight of Evidence:

$$\text{WoE} = \ln \left( \frac{N_i}{P_i} \right) - \ln \left( \frac{\sum N_i}{\sum P_i} \right)$$

- Variable selection: 79 variables, 15 selected for non-start-ups and 12 selected for Start-ups

	Non-start-ups	start-ups
Number of variable selected by at least <b>one</b> year's logistic regression	41	37
Number of variable selected by at least <b>two</b> year's logistic regression	24	24
Number of variable selected by at least <b>three</b> year's logistic regression	13	11
Number of variable selected by all <b>four</b> year's logistic regression	10	5

# Panel data models

- Model building:

Logit panel model: outcomes fall between 0 and 1

Using same variables as logistic regression

Omitted variables:

Soft information

Business cycles

Fixed effect or random effect for firm specific omitted variables

# Logit panel model

- Logit panel data model:

$$\Pr(y_{it} = 1 | X_{it} = x_{it}) = \frac{\exp(\beta x_{it} + \alpha_i + \delta_t + u_{it})}{1 + \exp(\beta x_{it} + \alpha_i + \delta_t + u_{it})}$$

- Fixed Effects:

$$\Pr\left(y_i \mid \sum_{t=1}^{T_i} y_{it} = k_{1i}\right) = \frac{e^{\sum_{t=1}^{T_i} y_{it} x_{it} \beta}}{\sum_{q \in S_i} e^{\sum_{t=1}^{T_i} y_{it} x_{it} \beta}} = f_i(T_i, k_{1i})$$

- Small Variation Within independent variables
- Customers with no change in dependent variables are moved out of estimation: 170,354 observations removed for non-start-ups and only use the left 33.9% for estimation
- Hausman: both estimators should be **consistent**
- Assume: soft information is independent of existing variables

# Logit panel model

- Random effects:  $c_i \sim N(0, \sigma_c^2)$

- Assuming  $\Pr(y_{i1}, y_{i2}, \dots, y_{in} | x_{i1}, x_{i2}, \dots, x_{in}) = \int \frac{e^{-c_i^2} / 2\sigma_c^2}{\sqrt{2\pi\sigma_c}} \left\{ \prod_{t=1}^n F(y_{it}, x_{it}\beta + c_i) \right\} dc_i$

then

$$F(y, z) = \begin{cases} \frac{1}{1+e^{-z}}, & z \neq 0 \\ \frac{1}{1+e^z}, & z = 0 \end{cases}$$

$$l_i = \int \frac{e^{-c_i^2} / 2\sigma_c^2}{\sqrt{2\pi\sigma_c}} \left\{ \prod_{t=1}^n F(y_{it}, x_{it}\beta + c_i) \right\} dc_i = \int g(y_{it}, x_{it}, c_i) dc_i$$

Which will be estimated by M-point Gauss-Hermite quadrature

# Adding Macroeconomic Variables (MVs)

## MVs movement through the latest crisis



# Adding Macroeconomic Variables

- Figlewski(2010) MVs' influence on US cooperations' default: three group of macroeconomic variables ( direction of economy, general economic conditions, financial market.)
- Previous research on credit card scoring using MVs
- lags
  - First: no lag
  - Averaged macroeconomic variables:

$$X_t = \frac{\sum_{K=0}^2 \delta^K X_{t-k}}{\sum_{K=0}^2 \delta^K}$$

where  $\delta=0.88$ , and  $k = 0, 1, 2$ .

# Influence of MVs

segments		Start-ups			Non-start-ups		
lags		no lag		Averaged	no lag		Averaged
	MV	one at a time	Best AIC set	Best AIC set	one at a time	Best AIC set	Best AIC set
Direction of economy	GDP growth rate	+	+	+	+	+	+
General economic conditions	CPI rate	-			-		
	unemployment rate	-	-	-	-	-	-
Financial market condition	FTSE100 index changing rate	+	+	+	-	+	+
	FTSEall share index changing rate	+			-		

# Correlation within MVs

NON-START-UPS					
	GDP growth rate	CPI changing rate	Unemployment rate	FTSE all share annual return	FTSE100 annual return
GDP growth rate	1				
CPI changing rate	0.075	1			
Unemployment rate	-0.4393	-0.1853	1		
FTSE all share annual return	-0.1489	-0.7448	0.7627	1	
FTSE100 annual return	-0.0974	-0.7744	0.7193	0.9977	1
START-UPS					
	GDP growth rate	CPI changing rate	Unemployment rate	FTSE all share annual return	FTSE100 annual return
GDP growth rate	1				
CPI changing rate	-0.0967	1			
Unemployment rate	-0.4943	-0.1642	1		
FTSE all share annual return	-0.069	-0.775	0.7199	1	
FTSE100 annual return	-0.0084	-0.8073	0.6691	0.9973	1

# Pooled Estimator V.S. Panel Estimators

- **Likelihood ratio test:** whether RE estimator is different from pooled estimators:

$$\rho = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\epsilon^2}$$

denote panel level variance as  $\sigma_v^2$ ,  $\sigma_\epsilon^2$  is the normal residual.

- If  $\rho$  is not significantly different from zero, then we cannot reject the hypothesis that panel estimators is the same as pooled estimators
- Logit panel models **only** using same variable as logistic regression: no difference with pooled estimator
- Logit panel models using same variable as logistic regression **and time influence (dummy or MVs)**: different from pooled estimator

# Model Comparison

- Training sample: ROC
  - 2007-2010, 10% of original data

non-start-ups					
	Test Result Variable(s)	AUROC			
		2007	2008	2009	2010
logistic regression	pd_log	.819	.855	.894	.859
panel model	pd_pan	.802	.843	.888	.850
panel model with year dummy	pd_pandum	.819	.855	.893	.860
panel model with selected no lagged MV (highest AIC in each category)	pd_L0B3	.819	.855	.893	.860
panel model with selected one year lagged MV (highest AIC in each category)	pd_L1B3	.819	.855	.893	.860
panel model with selected averaged MV (highest AIC in each category)	pd_AVB3	.819	.855	.893	.860
panel model with no lagged GDP_growth rate	pd_L0GDP3	.804	.855	.889	.852
panel model with one year lagged GDP_growth rate	pd_L1GDP3	.805	.855	.889	.853
panel model with averaged GDP_growth rate	pd_AVGDP3	.819	.855	.893	.860

# Model Comparison

- Training sample: ROC
  - 2007-2010, 10% of original data

start-ups					
	Test Result Variable(s)	AUROC			
		2007	2008	2009	2010
logistic regression	pd_log	.777	.827	.878	.832
panel model	pd_pan	.784	.829	.880	.837
panel model with year dummy	pd_pandum	.784	.829	.881	.837
panel model with selected no lagged MV (highest AIC in each category)	pd_L0B3	.794	.838	.886	.847
panel model with selected one year lagged MV (highest AIC in each category)	pd_L1B3	.794	.838	.886	.847
panel model with selected averaged MV (highest AIC in each category)	pd_AVB3	.794	.838	.886	.847
panel model with no lagged GDP_growth rate	pd_L0GDP3	.778	.836	.885	.839
panel model with one year lagged GDP_growth rate	pd_L1GDP3	.773	.835	.883	.837
panel model with averaged GDP_growth rate	pd_AVGDP3	.794	.837	.886	.847

# Model Comparison

- Holdout Sample: ROC
  - 2010 original data exclude training sample

	Area Under the Curve			
	non		st	
logistic regression	pd_log	.837	pd_log	.753
panel model	pd_pan	.828	pd_pan	.757
panel model with year dummy	pd_pandum	.843	pd_pandum	.769
panel model with selected no lagged MV (highest AIC in each category)	pd_L0B3	.843	pd_L0B3	.758
panel model with selected one year lagged MV (highest AIC in each category)	pd_L1B3	.843	pd_L1B3	.758
panel model with selected averaged MV (highest AIC in each category)	pd_AVB3	.843	pd_AVB3	.758
panel model with no lagged GDP_growth rate	pd_L0GDP3	.833	pd_L0GDP3	.759
panel model with one year lagged GDP_growth rate	pd_L1GDP3	.832	pd_L1GDP3	.758
panel model with averaged GDP_growth rate	pd_AVGDP3	.842	pd_AVGDP3	.758

**Thank you!**

Q&A