

# Financial Constraints and Firm Dynamics

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# Outline

- 1 Introduction & data
  - Motivation
  - Aim of the paper
  - Data description
- 2 Firm size distribution, age and financial constraints
- 3 Analytical framework
- 4 Robustness checks

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# Available evidence on FCs and firms' dynamics

- 1 **structured / complex impact of FCs**: FCs affect many dimensions of firms' decisions and evolution
  - investment/divestment decisions
  - decision to expand production or entering new markets
  - cash management
  - R&D policies . . .
- 2 Qualitative evidence on reaction to crises (Campello, Graham and Campbell, NBER2009) suggests **heterogenous impact of FC**:
  - “Pinioning effect”: firms facing good opportunities tend to bypass attractive investment projects
  - “Loss reinforcing” effect: firms facing poor growth opportunities display higher propensity to sell off productive assets to generate funds, further deteriorating growth prospects

# Empirical background: regression analyses

Long tradition of studies on the effects of FC on firms' decisions and evolution

- FC is a significant determinant of firms' investment decisions: Fazzari, Hubbard and Petersen, Brooking Papers(1988).
- FC has impact on firm growth: Deveraux and Schiantarelli, NBER WP(1990); Becchetti and Trovato, SBE(2002); Desai, Gompers and Lerner, NBER WP(2003).

Traditional approach: augmented Gibrat's regression

$$s_t - s_{t-1} = c + \lambda s_{t-1} + \beta \text{FC-Proxy} + \epsilon_t$$

Limitation 1: it captures central effect of FCs on growth

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# Empirical background: distributional analyses

## ① Cabral and Mata, AER(2003)

- FSD of a cohort is skewed at time of birth and gradually evolve toward more symmetric distribution
- The evolution of FSD is determined by firms ceasing to be FC

## ② Angelini and Generale, AER(2008)

- negative relation between FC and firm size: FC firms are smaller and their FSD is more skewed; FC matter only for a small group of firms (~5.8% of their database)
- FC is not the main determinant of the FSD evolution

Limitation 2: They ignore the relation between short-run and long-run effects of FS

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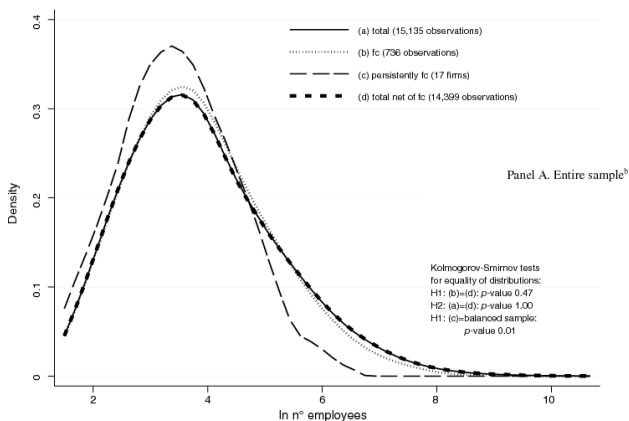
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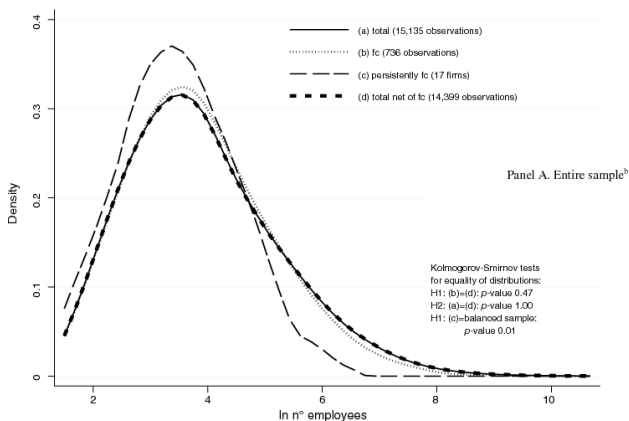
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# What you (hopefully) get by reading this paper

There are remarkable effects of FCs on firms' growth that are overlooked in a standard regression analysis framework. These effects have a sound economic interpretation.

To identify them we

- 1 move beyond the traditional regression approach and account for
  - non-normal growth shocks
  - non linear heteroskedastic effects
- 2 focus on **distributional properties** of growth allowing FCs to affect differently
  - growing and not-growing firms (**check for induced asymmetries**)
  - fast growing firms with respect to slow growing one (**look at the tails of the distribution**)

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# Data description

**DATA SET:** sample from the Italian CADS - Company Account Data Service, including annual reports for approximately 165,000 *limited liability* firms, active in Manufacturing over the period 2000-2003. Cover 50% of total employment, 60% of Valued Added and around 7% in terms of number of firms.

**DATA PROVIDER:** CEBI founded as an agency of the Bank of Italy and the Italian Banking Association in the early 80's with the institutional task of monitoring risk exposure of Italian banking system. It is nowadays a private company owned by major Italian banks.

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# Cleaning and data selection

Few anomalous observations are removed. **Details.**

Variable considered are SIZE (Total sales), ASSETS (Net tangible assets), PROFIT (Gross operating margin) and CEBI **rating index**:

- Rating score in the range 1-9 but not cardinal
- built using multivariate discriminant analysis: firms expected ability to pay back their loans
- higher score firms are smaller, more leveraged and they pay higher interest rates. (Panetta, Schivardi and Schum, 2009 JMCB).

FC proxy built using CEBI rating

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# Using rating as FC proxy

- 1 Similarly to recently developed multivariate indexes of FCs (Cleary, JF 1999; Lamont, Polk and Saá-Requejo, RFS 2001), credit ratings meet 3 crucial conditions:
  - provide a multidimensional assessment of firms' financial position
  - allow to avoid a simple binary categorization into constrained vs. not constrained firms
  - vary over time.
- 2 Alternative in the literature are survey based measures:
  - suffer from mis-perception and/or self-selection biases
  - capture the opinion of the “credit seekers” on “credit suppliers”, while the opposite direction seems more relevant
- 3 CEBI rating vs. other ratings:
  - available for ALL firms in the data
  - due to institutional role of CeBi, we know banks rely on CeBi ratings in granting and pricing credit to firms

# FC classification

Three FC classes:

- **Non Financially Constrained (NFC)**, rating in 1-4.
- **Mildly Financially Constrained (MFC)**, rating in 5-7.
- **Highly Financially Constrained (HFC)**, rating in 8-9.

Assignment based on the rating of the previous year (we also explored **other possibilities**).

Data pooled together after checking results are stationary.

FC classes are weakly related with economic variables but they affect probability of financial distress.

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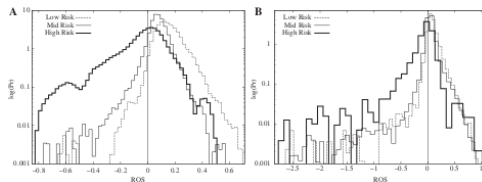
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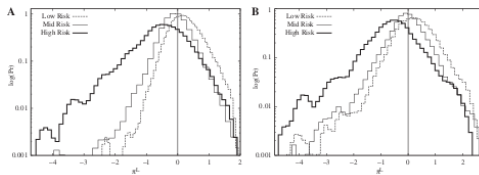


# Rating and economic variables 1

from *Productivity, Profitability and Financial Performance* by Bottazzi, Tamagni and Secchi, ICC 2008



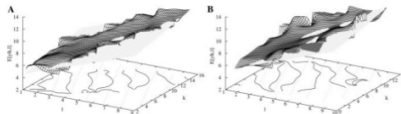
**Figure 2** Empirical density of ROS in 2002 for the manufacturing (A) and service (B) industry.



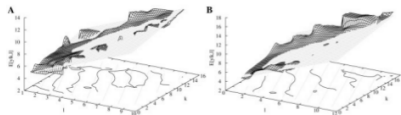
**Figure 4** Empirical density of labor productivity differentials in 2002 for the manufacturing (A) and service (B) industry. Labor productivity is defined as VA/L.

# Rating and economic variables 2

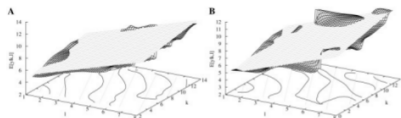
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**Figure 6** Kernel estimates of the conditional expectation of output: Low-Risk firms in service (A) and in manufacturing (B)—2002. Sectoral plane via OLS.



**Figure 7** Kernel estimates of the conditional expectation of output: Mid-Risk firms in service (A) and in manufacturing (B)—2002. Sectoral plane via OLS.



**Figure 8** Kernel estimates of the conditional expectation of output: High-Risk firms in service (A) and in manufacturing (B)—2002. Sectoral plane via OLS.

# Rating and firm default

from *Financial and Economic Determinants of Firm Default* by Bottazzi, Grazzi, Secchi and Tamagni, JEE 2010

**Table 6** Probit estimates of default probabilities including credit ratings as modeled in Eqs. 10 and 11—results over 200 bootstrap replications

	Bootstrap probit with credit ratings—estimates by year							
	Rating only				Rating, financial and economic			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1999	2000	2001	2002	1999	2000	2001	2002
<b>Panel A: estimates</b>								
IE/S					0.0039*	0.0041*	0.0049	0.0088*
LEV					-0.0001	-0.0013	-0.0015	0.0028*
FD/S					0.0044	0.0059	0.0026	0.0019
ln SIZE					0.0061*	0.0072*	0.0090*	0.0086*
PROD					-0.0111*	-0.0075*	-0.0059*	-0.0011
PROF					-0.0004	-0.0015	-0.0021	-0.0037*
GROWTH					0.0054*	-0.0000	-0.0038*	-0.0036*
CONSTANT	-0.3694*	-0.4770*	-0.3720*	-0.1628*	-0.4999*	-0.6582*	-0.4960*	-0.3021*
LOW	-0.0301*	-0.0076	-0.0323*	-0.1206*	0.0001	0.0186*	-0.0047	-0.0428*
MID	0.0198*	0.0614*	0.0414*	-0.0072	0.0392*	0.1134*	0.0639*	0.0068
<b>Panel B: model performance</b>								
Brier score	0.0328	0.0327	0.0322	0.0319	0.0325	0.0326	0.0320	0.0316
Threshold	0.0258	0.0284	0.0193	0.0163	0.0290	0.0254	0.0239	0.0270
Type I error	78.0000	70.7850	61.0700	48.7550	36.6350	30.0450	29.8300	25.8250
Type II error	576.1900	616.3500	709.3900	633.7250	1,248.9350	1,334.5550	1,230.2100	901.1550
% Correct default	0.3906	0.4757	0.5606	0.6278	0.7138	0.7774	0.7854	0.8029
% Correct non default	0.8397	0.8361	0.8171	0.8262	0.6526	0.6452	0.6828	0.7528
<b>Panel C: comparisons of prediction performance against the "rating only" model of the same year</b>								
Threshold					0.0258	0.0284	0.0193	0.0163
Type I error					25.2550	39.5450	16.2850	11.8150
Type II error					1,612.8600	1,111.9150	1,722.5850	1,507.6900
% Correct default					0.8027	0.7071	0.8828	0.9098
% Correct non default					0.5514	0.7044	0.5558	0.5865

Variables are in z-scores. *Panel A*: Bootstrap means of marginal effects at the sample average of covariates. \*Significant at 1% level. *Panels B and C*: Bootstrap means of model performance measures



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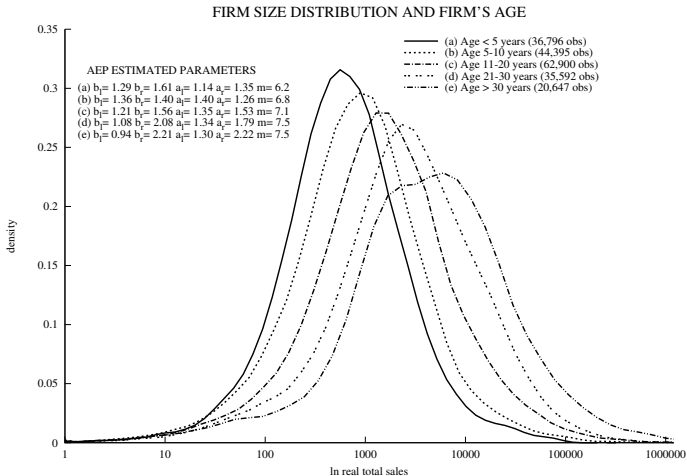
# Relevance of the FC phenomenon

Table: FINANCIAL CONSTRAINTS BY AGE CLASSES

Firm's age (years)	Whole Sample		Non Financially Constrained		Mildly Financially Constrained		Highly Financially Constrained	
	Number of firms	Size: mean (median)	Number of firms (% age class)	Size: mean (median)	Number of firms (% age class)	Size: mean (median)	Number of firms (% age class)	Size: mean (median)
0-4	38,020	1.795 (0.606)	10,356 (27.2)	1.804 (0.525)	20,408 (53.7)	1.970 (0.719)	7,256 (19.1)	1.293 (0.449)
5-10	52,150	3.369 (0.860)	18,269 (35.0)	4.115 (0.844)	27,862 (53.4)	3.248 (0.995)	6,019 (11.5)	1.666 (0.439)
11-20	62,977	7.093 (1.522)	29,130 (55.9)	8.210 (1.606)	29,408 (46.7)	6.400 (1.663)	4,439 (7.0)	4.354 (0.525)
21-30	35,579	10.139 (2.674)	18,966 (53.3)	11.147 (2.719)	15,080 (42.4)	9.544 (2.921)	1,533 (4.3)	3.520 (0.696)
31-∞	20,645	25.917 (4.516)	11,374 (55.1)	26.600 (4.919)	8,213 (39.8)	22.157 (4.764)	1,058 (5.1)	47.760 (1.345)
Total	209,371	7.577 (1.301)	88,095 (42.1)	9.614 (1.548)	100,971 (48.2)	6.386 (1.371)	20,305 (9.7)	4.662 (0.494)

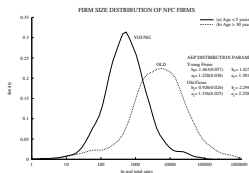
<sup>a</sup> Size as real sales, millions of euro.

# FSD and age

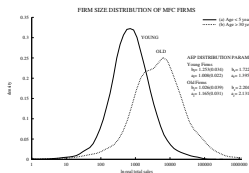


## FSD, age and financial constraints

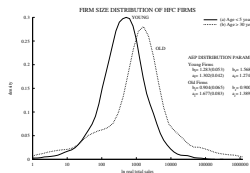
## NFC



## MFC



## HFC



FSD evolution depends on the FC class:

- shift in the central location, smaller for the HFC class
- variance increases for NFC and MFC, less for HFC See stats
- right-tail tends to Gaussian for NFC and MFC, not for HFC  
Asymmetric Power Exponential(AEP)

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# Augmented Gibrat's process

$$s_t = s_{t-1} + \epsilon_t$$

Gibrat's benchmark is a good first approximation: seems good for NFC and MFC but not for HFC.

# Augmented Gibrat's process

$$s_t - s_{t-1} = c + \lambda s_{t-1} + \sigma(s_{t-1})\epsilon_t$$

Gibrat extended to include:

- Autoregressive coefficient  $\lambda$
- Heteroskedastic correction  $\sigma$
- Non-normality  $\epsilon$  Asymmetric Laplace (ALAD regression)

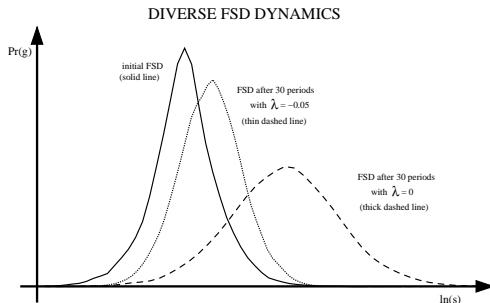
## Augmented Gibrat's process

$$s_t - s_{t-1} = c_{FC} + \lambda_{FC} s_{t-1} + \sigma_{FC}(s_{t-1})\epsilon_t$$

Allow the coefficient to vary across FC classes: drop orthogonality assumption of residuals and partially solve omitted variable bias

## The effect of $\lambda$

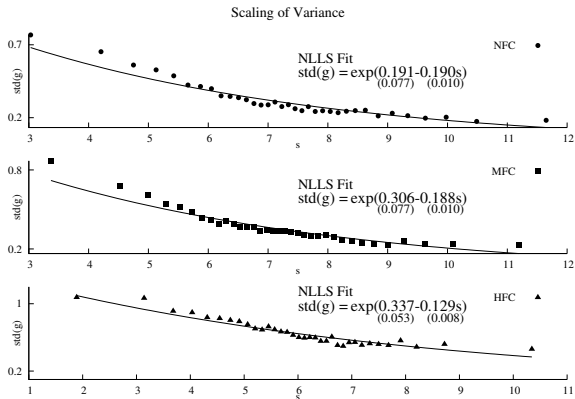
Different values of  $\lambda$  imply different evolutions of the FSD:



Given the barrier effect of FCs suggested by all previous analysis, we expect  $\lambda < 0$ , and thus NON Log-normal FSD, for more severely constrained firms

# The need of $\sigma(s)$

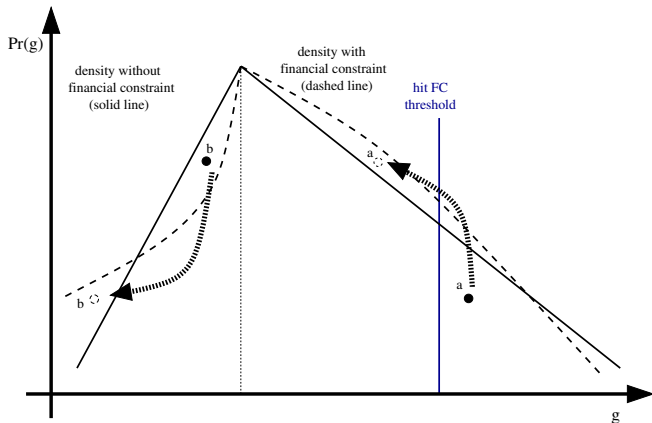
Often reported negative relation between the variance of growth  $g_{i,t} = s_{i,t+1} - s_{i,t}$  and size. Exponential fit (N.B.: does not depend on age)



# FCs and the distribution of growth rates

Qualitative evidence: “pinioning” and “loss reinforcing”

## ASYMMETRIC DISTRIBUTIONAL EFFECT



# Regression Analysis

We end up with Model 1

$$s_t - s_{t-1} = c_{FC} + \lambda_{FC} s_{t-1} + \exp(\gamma_{FC} \cdot s_{t-1}) \epsilon_{FC,t}$$

estimated through ALAD.

	FC CLASS	Model 1
	<u>NFC</u>	
$\gamma$		-0.222*(0.001)
c		0.009*(0.001)
$\lambda$		-0.0007*(0.0003)

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	<u>MFC</u>	
$\gamma$		-0.220*(0.001)
c		-0.011*(0.001)
$\lambda$		-0.0076*(0.0003)

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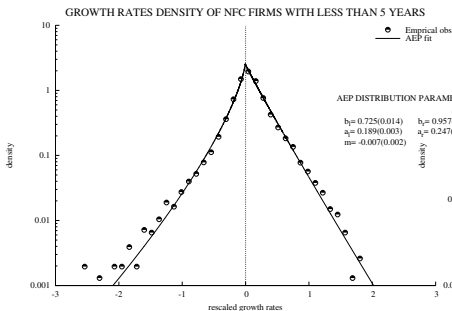
	<u>HFC</u>	
$\gamma$		-0.161*(0.002)
c		-0.013*(0.003)
$\lambda$		-0.030*(0.001)

\* significantly different from zero at 1%. Sandwich errors.

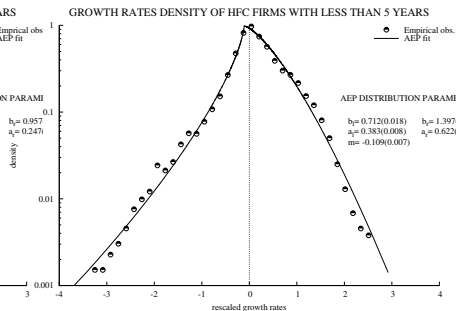


# Distribution of residuals by FC class: young firms

## YOUNG NFC



## YOUNG HFC

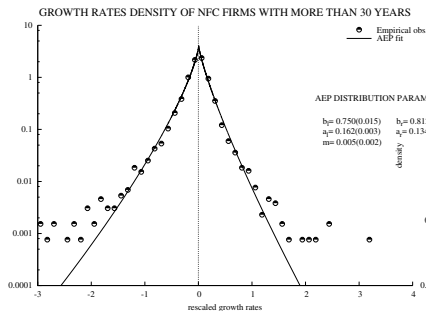


For younger firms, strong FCs :

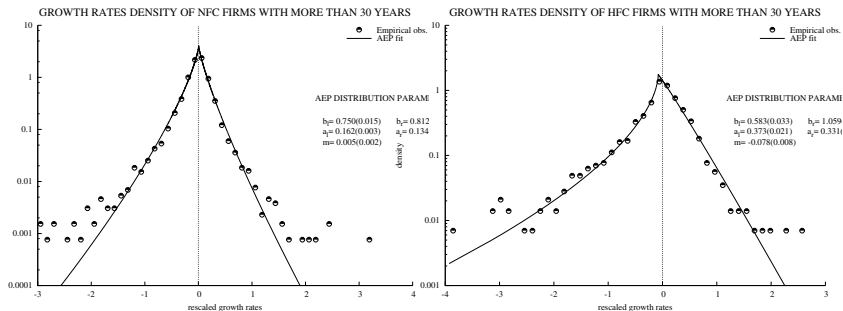
- slim down the right tail of the distribution, i.e. shift of probability mass from the tail to the central part of the distribution
- do not seem to have an effect on the left half

# Distribution of residuals by FC class: old firms

## OLD NFC



## OLD HFC



For old firms, strong FCs:

- imply a very mild slim down of the right tail
- fatten up the left tail of the distribution, i.e. shift of probability mass from the central part to the tail of the distribution

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# Attrition from sample censoring

**Problem:** higher exit rates for smaller firms + size relation  $n$  with FC  $\rightarrow$  bias in  $\lambda$ .

**Solution:** split the sample in size classes (Eurostat def. in num. of emplo.) and re-estimate Model I.

	Micro(0-9)	Small(10-49)	Medium(50-249)	Large(250+)
<u>NFC</u>				
$\gamma$	-0.2520(0.0014)	-0.1196(0.0045)	-0.1591(0.0052)	-0.1098(0.0104)
$c$	0.0056(0.0009)	0.0095(0.0010)	0.0009(0.0011)	-0.0058(0.0024)
$\lambda$	-0.0115(0.0006)	-0.0114(0.0013)	-0.0064(0.0013)	-0.0024(0.0022)
<u>MFC</u>				
$\gamma$	-0.2407(0.0015)	-0.1707(0.0042)	-0.1704(0.0056)	-0.2307(0.0131)
$c$	-0.0171(0.0009)	-0.0117(0.0013)	-0.0142(0.0015)	-0.0290(0.0040)
$\lambda$	-0.0220(0.0007)	-0.0308(0.0015)	-0.0102(0.0017)	-0.0057(0.0034)
<u>HFC</u>				
$\gamma$	-0.1715(0.0029)	-0.2219(0.0136)	-0.1995(0.0192)	-0.1339(0.0213)
$c$	-0.0067(0.0031)	-0.1264(0.0080)	-0.0366(0.0121)	-0.0916(0.0217)
$\lambda$	-0.0736(0.0023)	-0.1272(0.0085)	-0.0630(0.0116)	-0.0141(0.0128)

## Confounding factors

**Problem:** important variables related to growth and FC left out → biased estimates

**Solution:** augment regression with age, usually correlated with size; GOM=max{gross operating margins, 1}, availability of internal resources; ASSETS=net tangible assets, collaterals; to obtain Model 2A

$$s_t - s_{t-1} = c_{FC} + \lambda_{FC} s_{t-1} + \beta_{1FC} \ln(\text{age}_t) + \beta_{2FC} \ln(\text{GOM}_{t-1}) + \beta_{3FC} \ln(\text{ASSETS}_{t-1}) + \exp(\gamma_{FC} s_{t-1}) \epsilon_{tFC}$$

We include sectoral dummies following Pavitt taxonomy, Hall OReOP(2002) to obtain Model 2B

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We include sectoral dummies following Pavitt taxonomy, Hall OReOP(2002) to obtain Model 2B

	FC CLASS	Model 1	Model 2A	Model 2B
	<u>NFC</u>			
$\gamma$		-0.222*(0.001)	-0.207*(0.001)	-0.208*(0.001)
c		0.009*(0.001)	0.017*(0.001)	0.015*(0.001)
$\lambda$		-0.0007*(0.0003)	-0.008*(0.001)	-0.008*(0.001)
$\ln(\text{Age}_{i,t})$			-0.023*(0.001)	-0.023*(0.001)
$\ln(\text{ASSETS}_{i,t-1})$			0.021*(0.001)	0.020*(0.001)
$\ln(\text{GOM}_{i,t-1})$			0.002(0.001)	0.002(0.001)
	<u>MFC</u>			
$\gamma$		-0.220*(0.001)	-0.205*(0.001)	-0.205*(0.001)
c		-0.011*(0.001)	0.003*(0.001)	-0.007*(0.001)
$\lambda$		-0.0076*(0.0003)	-0.018*(0.001)	-0.018*(0.001)
$\ln(\text{Age}_{i,t})$			-0.040*(0.001)	-0.040*(0.001)
$\ln(\text{Assets}_{i,t-1})$			0.028*(0.001)	0.027*(0.001)
$\ln(\text{GOM}_{i,t-1})$			0.009*(0.001)	0.010*(0.001)
	<u>HFC</u>			
$\gamma$		-0.161*(0.002)	-0.143*(0.002)	-0.143*(0.002)
c		-0.013*(0.003)	0.023*(0.003)	0.014*(0.003)
$\lambda$		-0.030*(0.001)	-0.052*(0.002)	-0.052*(0.002)
$\ln(\text{Age}_{i,t})$			-0.125*(0.003)	-0.127*(0.003)
$\ln(\text{Assets}_{i,t-1})$			0.066*(0.003)	0.064*(0.003)
$\ln(\text{GOM}_{i,t-1})$			0.019*(0.002)	0.021*(0.002)

\* significantly different from zero at 1%. Sandwich errors.

## Sum up

In summary, we have shown that FC problems do have relevant effects on the operating activities of firms. In order to identify these effects, however, one has to do more work than just relying upon standard linear regression framework. FC effects are indeed manifold and impact on several aspects of firm growth dynamics, ranging well beyond a shift in the expected growth rates.



## Data details

Data cleaned by Total Sales: for each firm a “nan” has been inserted instead of the original Total Sales value when the latter lied outside the interval

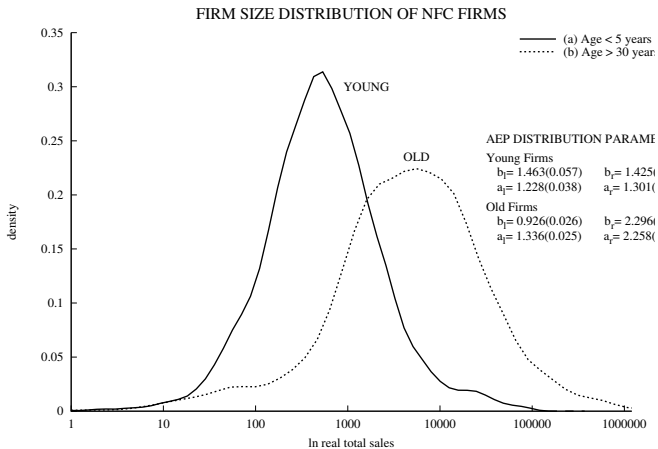
$$[\text{Median}(\log(TS_t))/10, \text{Median}(\log(TS_t)) * 10] \quad t = 1998, \dots, 2003$$

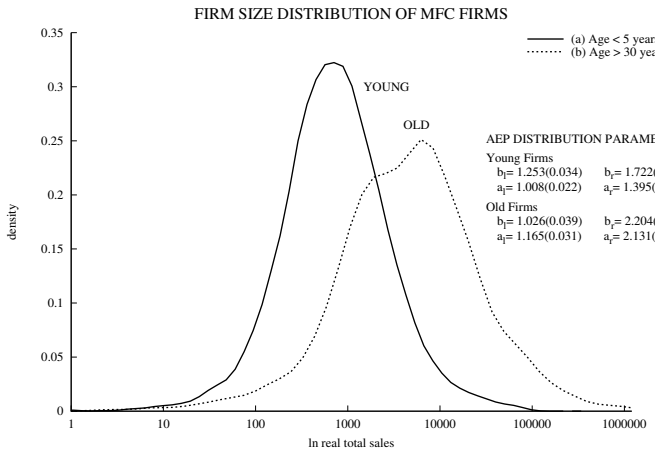
[Back.](#)

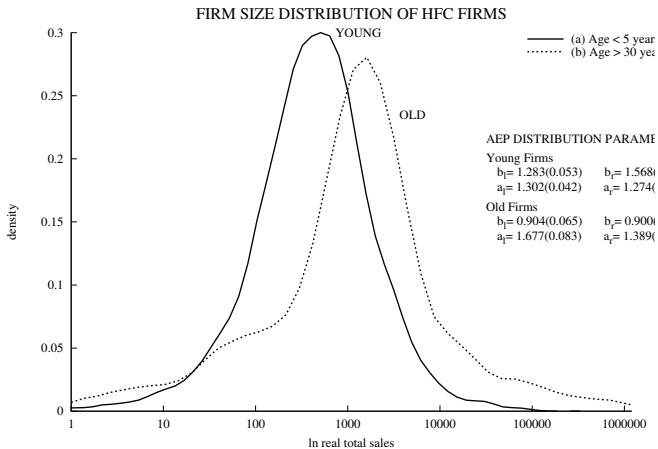
Tried different assignment procedures:

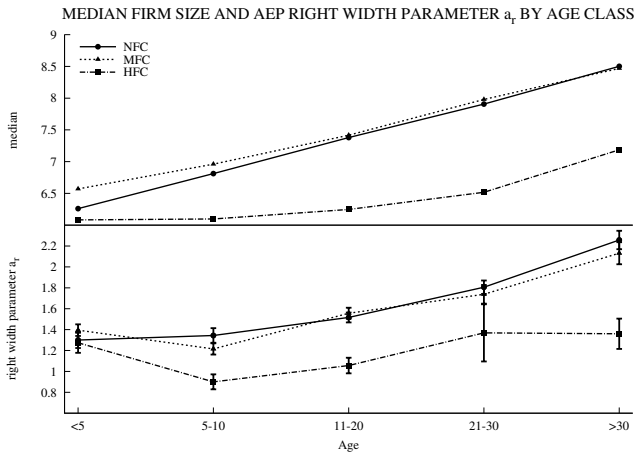
- **Lag 1:** Based on the rating of the previous year
- **The worst:** Based on the worst rating obtained by the firm over the whole time window
- **Persistent:** Assigned only if a firm does not change its financial status over the whole time window

Results are qualitatively robust against assignment procedures. [Back](#)









## Asymmetric Power Exponential distribution

$$f_{AEP}(x; \mathbf{p}) = \frac{1}{C} e^{-\left(\frac{1}{b_l} \left|\frac{x-m}{a_l}\right|^{b_l} \theta(m-x) + \frac{1}{b_r} \left|\frac{x-m}{a_r}\right|^{b_r} \theta(x-m)\right)}$$

where  $\mathbf{p} = (b_l, b_r, a_l, a_r, m)$ ,  $\theta(x)$  is the Heaviside theta function and  $C$  the normalization constant. **Back**

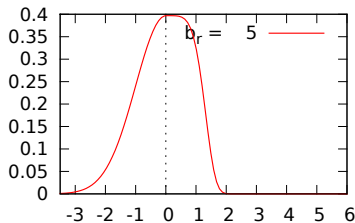
$b_l=2, b_r=\{5,1,0.5\}, a_l=1, a_r=1, m=0$

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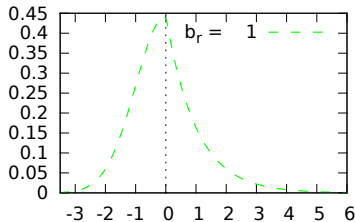


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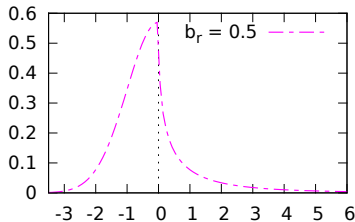


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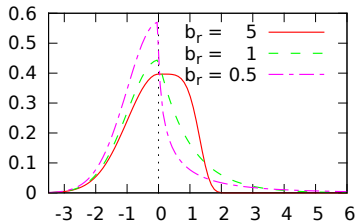


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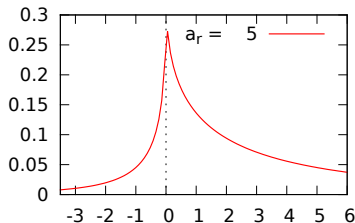
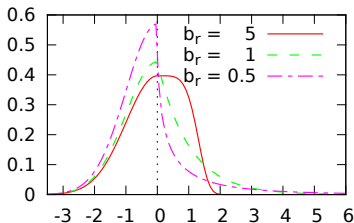
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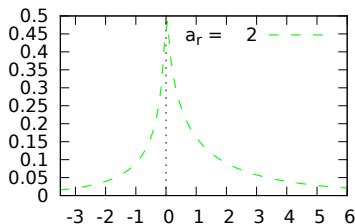
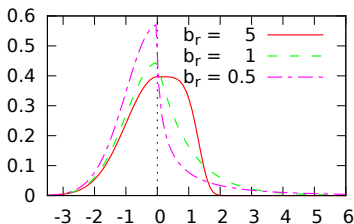
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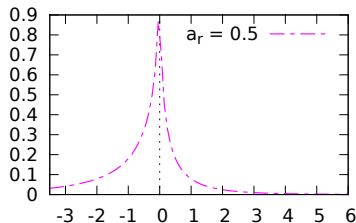
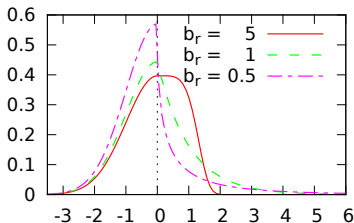
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