The Shadow of Death Unmasked: Characterizing the Growth Process of Defaulting Firms

M. Molinari

Abstract In this paper we characterize patterns observed for defaulting firms *vis-à-vis* non-failed firms along three dimensions: long-run solvency, profitability and financial pressure. Our results suggest that defaulting firms appear to be structurally weaker than viable firms. Such weaknesses is well documented by both the profile analysis and the turbulence found in the failing firms' transition dynamics. The evidence gathered in this work suggests that default dynamics unfold relatively quickly. Defaulting firms are on average more financially fragile firms already, and the shadow of death is detectable even 5 years prior to default in financial structure. Yet, this weakness does not have a contemporaneous negative knock-on effect on growth. Indeed, the average failing firm is performing in terms of growth rates as well as the viable firms up to to 2001. A tentative explanation would be that such firms survive until a negative (demand) shock hit them, and when that happens, both their financial and productive apparatus break down. What matters for growth is first a sharp decline in operating profitability in the year prior to default and net-worth plummets in the year of default. There is little evidence instead that financial pressure curtails growth defaulting firms to a greater extent. As a matter of fact, financial pressure exerts a negative effect on growth, but the impact is constant over time and this effect does not appear to be stronger for failing firms. This is true when we consider the growth of total assets. For sales and employment financial pressure (though higher) has a different effect. We observe that in the last year sales growth is actually positively affected by the increasing financial pressure, whereas the latter one elicits a negative effect on employment growth. This suggests that the three growth rates do not always move together in the same direction and they may respond differently to the same financial shock. If this was the case, a trade-off may possibly arise and this may become stronger in a situation of distress, as in our case, or more generally during a recession phase.

Keywords Default · Firm Growth · Financial Structure.

JEL Codes: D22 · G32 · L25

Manuscript drafted for the SIE (Italian Economic Association) 56^{th} annual conference

Massimo Molinari
Department of Economics and Law
Sapienza University of Rome
Via del Castro Laurenziano, 9 - 00161 Rome (IT)
Tel:+39 06 49766403
E-mail: massimo.molinari@uniroma1.it

1 Introduction and Motivations

The main purpose of this paper is to use the analysis of financial ratios to characterize the dynamics of defaulting firms. The prediction of corporate failure based on financial ratios is the topic of a long-lasting tradition of studies. A non exhaustive list of relevant contributions would certainly include Tamari (1966), Beaver (1966), Beaver (1968), Altman (1968), Wilcox (1971), Deakin (1972), Edminster (1972), Blum (1974), Dambolena and Khoury (1980) and Altman and Saunders (1997). The latter work offers an extensive for a review of the literature. More recently Bharat and Shumway (2008) rely on the notion of distance to default to predict bankruptcy and finally, Bottazzi et al. (2011b), improve the prediction accuracy by adding to financial ratios a set of economic variables including productivity and growth.[1]

The findings of the latter study in particular have prompted us to investigate more closely the relationship between growth and financial structure that characterizes defaulting firms.

Firm growth is now a well established field in industrial dynamics and research in this area has been pervasive.[2] Yet, the pre-exit patterns of defaulting firms has not been studied much in the industrial dynamics literature, whereas, there has been substantial research on post-entry performance.[3] What we know about exiting firms is associated to the so-called shadow-of-death effect. Griliches and Regev (1995) first introduce this terminology to convey the following idea: firms that exit the market do not collapse all of a sudden. On the contrary, they experience a constant decline of productivity detectable several years prior to the actual death of the firm. Griliches and Regev find evidence of this examining data on Israeli manufacturing firms. This evidence is consistent with the predictions of theoretical models on industrial dynamics such as Jovanovic (1982) or Hopenhayan (1992). In Jovanovic's model, for instance, firms are endowed with some given unknown productive efficiency and they learn their position by observing their realized profits. Those that learn to be inefficient shrink, whilst those that are efficient, will grow. In these models there is a close link between profitability and productivity and the model predict that those with low levels of productivity will not survive and their performance prior to exiting the market will fall below that of incumbent firms.

Some studies focused on the decline of firm size. Troske (1996) finds that defaulting firms display a constant decline in size up to 8 years before the exit. Wagner (1999) rejected this hypothesis using German data. Farinas and Ruano (2005) exploit data on Spanish firms to show that the productivity distribution of exiting firm is stochastically dominated by surviving firms. Carreira and Teixeira (2011) use information on manufacturing firms in Portugal and show how exiting firms display lower productivity, but they additionally show that there is a sizeable portion of firms that are ranked at the bottom of the distribution and yet do survive. They also note that some high-productivity firms fail. These findings seem to question the efficiency of the market selection mechanism, and clearly show that there is still much room for improvement in our understanding of exit dynamics.

Bellone et al. (2006) base their analysis on a sample of French firms operating in the manufacturing sector between 1900 and 2002. They also expand upon the previous works by adding a profitability measure. By comparing exiting firms with surviving firms, they confirm the existence of a significant and increasing differential in terms and productivity, profitability and size. Yet, they point out how the evolution of profitability is possibly the most relevant variable to determine firm exit. They also estimate the probability of exiting and find that once profitability is factored in, the significance of productivity is swept away.

This finding seems to suggest that the shadow of death effect could be best measured along this dimension, and the present work moves in this direction. In addition to profitability, we also add other financial variables and, by first examining patterns over time, we assess whether any shadow of death effect is detectable either in the growth performance, size or financial structure. Second, we characterize the relationships between financial status and growth of defaulting firms. Finally, we are going to character-

[1] Bottazzi et al. (2011b) exploit the same dataset that we use.

[2] See Coad (2009) for an extensive review on empirical works based on Gibrat's law regressions augmented version of such test. Recent works have enhanced our understanding of the empirical regularities in the structure of growth rates: see Bottazzi and Secchi (2006) on growth rates exhibiting fat tails, Bottazzi et al. (2002) on the properties of growth rate autocorrelation coefficients. Coad (2010a) investigates growth rates using vector auto-regression approach whereas, Coad (2007), applies quantile regression to growth rates to shed light on the growth process of fast-growing firms.

[3] See, for instance, Audretsch and Mata (1995).

ize with a regression based analysis the relationship between financial structure and growth for defaulting firms. More specifically we aim to understand to what extent financial structure is binding for such firms. We pursue this investigation in 3 ways: first, we assess whether the effect of financial structure and growth is constant over time or, as we expect, becomes stronger as the firm gets closer to the default date. Second, we explicitly assess whether the impact of financial structure on growth differs in any significant way between viable firms and defaulting firms. Third, we consider different measures of growth and we check whether they all respond in the same way to the deterioration in financial structure.

The remainder of this paper is organized as follows. In Section 2, we briefly introduced the variables of interest and then we examine patterns over time to assess whether any shadow of death effect is detectable either in the growth performance, size or financial structure. In Section 3, we compare the patterns by means of transition matrices whose states are defined with respect to the distribution of viable firms. Section 4 examines trough a regression-based analysis the extent to which growth is hampered by such a progressive deterioration of firms conditions along these three dimensions. We put forward some final remarks and conclude in Section 5.

2 Variables and Patterns over Time

Unicredit bank allowed us to add a new piece of information to our database: a small subset of firms (within the CeBi sample), costumers of Unicredit incurred default at the end of either 2003 or 2004.[4] This information is relevant as it allows the researcher to investigate a whole new set of issues related to financial distress. It is important to note that default now not necessarily mean failure. Some of these firms will be able to recover from a default state, so they do not necessarily leave the market. Yet, it could be argued that such firms are the most likely candidate to exit. The sample of defaulting firms comprises 108 firms continuously observed for 6 years preceding default.[5] Here we attempt to characterize a firm by looking at three different dimensions that we deem as important qualifiers of health-status of the firm. In the literature, there is ample evidence that liquidity, normally proxied by some cashflow-related measure, is positively associated to investment and growth. Yet, liquidity can be thought as the outcome of different factors and, especially in dealing with the context of defaulting firms, we feel that it is appropriate to focus on what could be reasonably deemed as the two main drivers of liquidity. As a rough approximation, liquidity is jointly determined by the ability to make profits - that should in turn depends on the relative efficiency of firm - and the burden of financial obligations. A firm can have little liquidity either because it is not making many profits, or because most of them are used up to settle previous financial obligations (typically interest charges on existing debt). Ideally, one would want to be able to disentangle the two different scenarios. To this end, we use ROS as operating profitability. This is by construction a measure of gross profitability. As such, it merely mirrors the production-based profitability of the firm and as such it should not be affected by financial costs, factors or policies.

Operating profitability is assessed together with a measure of financial pressure, defined by financial obligations scaled by total assets (COST). Finally, we use the equity ratio, defined as net-worth over total assets (EQ), as a measure of long-run solvency. The choice of the three variables is also consistent with the empirical evidence that liquidity/profitablity and solvency appear as the most relevant dimensions related to the prediction of corporate failure.[6] We start by tracking over time the performance of defaulting firms *vis-à-vis* the trend observed for viable firms kept as a natural benchmark. From now on, we shall refer to the sample of non-defaulting firms as group ND, and to the sample of defaulting firm as group D. First we look at the rates of growth, measured with respect to total assets, sales and employees. Rates of growth

[4] As pointed out in Bottazzi et al. (2011), since such information on the default event is available only for Unicredit costumers, it is likely to underestimate the real number of defaults in the sample. This could introduce a bias in studies related to the prediction of corporate failure. However, if the effectiveness of credit allocation is not believed to be dependent on the particular bank, we have no reason to believe that defaulting firms which are Unicredit costumers should be different from other defaulting firms. Hence the growth process of Unicredit defaulting firms should not display significant differences from the growth process of all defaulting firms in the CeBi sample.

[5] See the Appendix for a comparison with the unbalanced database. In the unbalanced panel, we have 108 firms observed for 6 years, 57 for 5 years, 30 for 4 years, 2 for 3 years, 3 for 2 years and 10 for 1 year only.

[6] See Altman (1968), Martikainen and Ankelo (1990).

have been computed as follows:

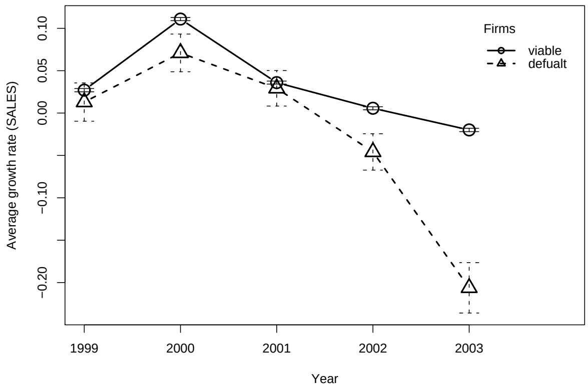
$$assets\_growth_{i,t} = ln(assets_{i,t}) - ln(assets_{i,t-1}) \tag{1}$$

$$sales\_growth_{i,t} = ln(sales_{i,t}) - ln(sales_{i,t-1}) \tag{2}$$

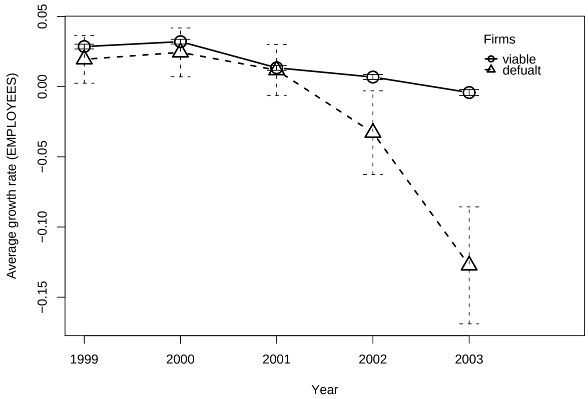
$$emp\_growth_{i,t} = ln(emp_{i,t}) - ln(emp_{i,t-1}). \tag{3}$$

Figures , and show the conditional average rate of growth over time with standard errors. It strikes the fact that rates appear to be fairly comparable up to 2001. As a matter of fact growth differentials only appear to emerge in 2002, and turn into a substantial gap only in 2003.

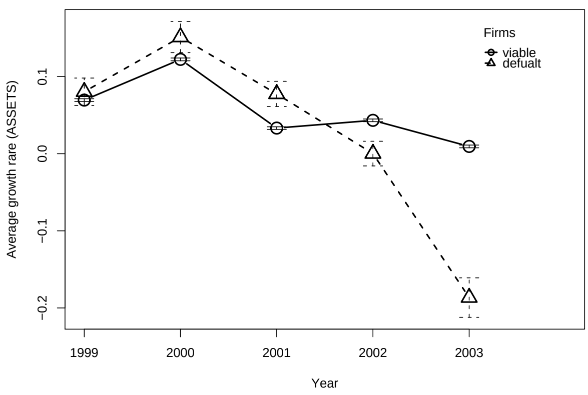
Fig. 1 Profile Analysis: Average Growth and Size and Financial Ratios over time (1)



$SALES_{GR}$

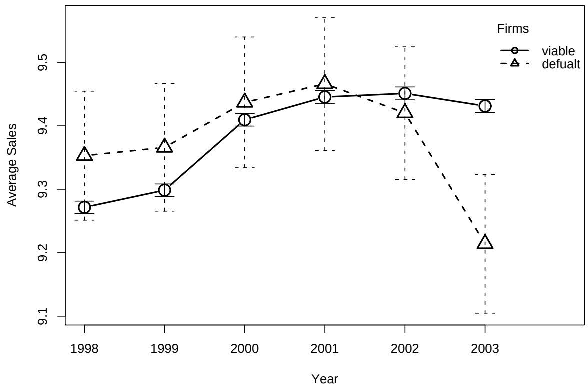


EMP_{GR}

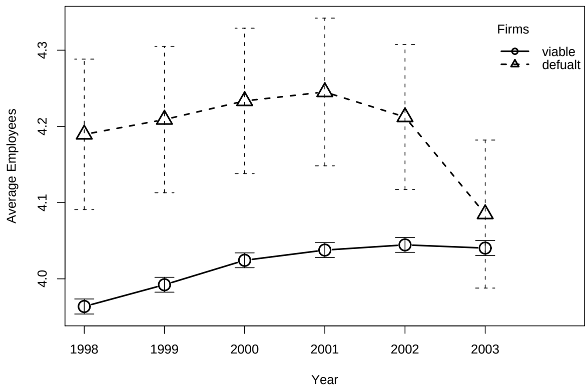


$ASSETS_{GR}$

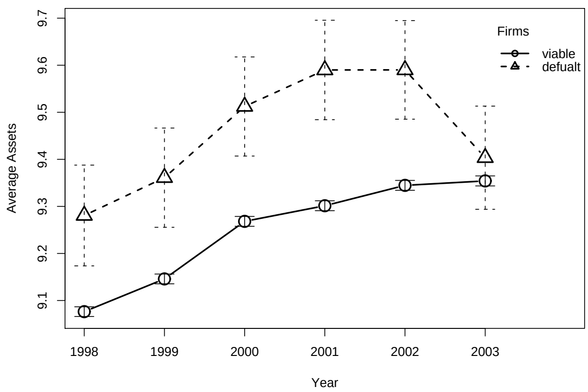
Fig. 2 Profile Analysis: Average Growth and Size and Financial Ratios over time (2)



$ln(SALES)$

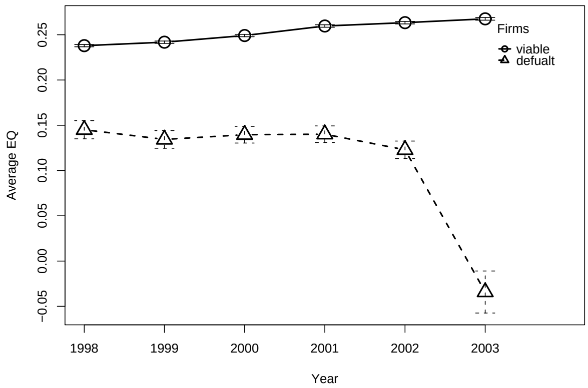


$ln(EMP)$

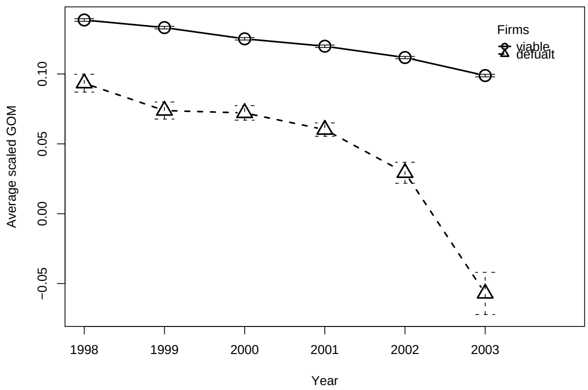


$ln(ASSETS)$

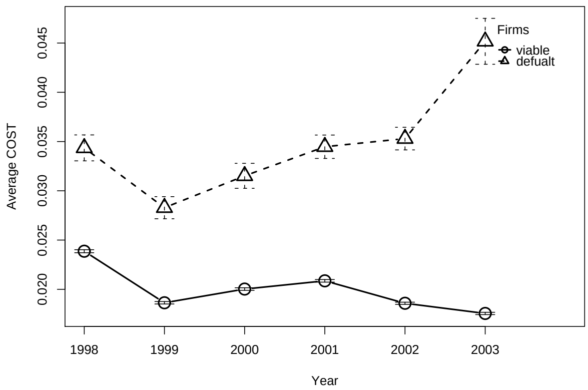
Fig. 3 Profile Analysis: Average Growth and Size and Financial Ratios over time (3)



EQ



ROS



COST

In other words, five years prior to default the performance of such firms was in line with that of non-defaulting firms, and a negative drift is recorded only one or two years prior to default. This is true regardless of the measure of growth adopted. Even more surprisingly, looking at , defaulting firms appear to be as large (in terms of sales) or possibly larger (in terms of employees and assets) than firms in group ND.

The picture that we have when we look at financial ratios is clearly different though. The properties and characteristics of financial ratios in viable firms have received considerable attention, and various studies provide evidence based on factor analysis to support the idea that financial patterns are relatively stable over time and across industries.[7]

Defaulting firms are structurally weaker than non-defaulting firms.[8] First, we see that, as for growth rates, the distance between the two groups increases substantially in 2003. Yet, such gap is evident even 6 years prior to the event of default and this is clearly the case for all the ratio considered. As a matter of fact, defaulting firms exhibit an equity ratio ten percentage points lower than viable firms already in 1998.

Defaulting firms also seem to be much more sensitive to the business cycle downturn, and their ability to make profits is heavily affected. Finally, financial pressure is increasing from 1999 onwards and, quite as expected, peaks in 2003. This evidence is consistent with the literature on corporate failure.

3 Transition Dynamics

In the previous section we provided *a prima facie* evidence that financial ratios for defaulting firms becomes unstable over time. This is consistent with previous results. Instability is found in different forms: for example, Martikainen and Ankelo (1990) resort to transformation analysis to assess the instability of financial patterns of failed firms and find that the interrelationships between financial variables are indeed more unstable for failed firms. They conclude that both the contents of factors and their empirical interpretation changes over time and this can affect the predictive ability of models designed on such factors. In addition, Dambolena and Khoury (1980) use a sample of failed and non-failed firms and adopt various measures of ratio stability to conclude that there is a significant difference between the two groups. In fact, they find that the former group of firms exhibit a substantial degree of instability over time as the corporation moves closer to the date of default. Such instability is best measured by an increasing standard deviation over time. The authors include such measure in the discriminant analysis performed to predict corporate failure and improve the accuracy of the model.

In the context of the present study, we further develop the notion of instability by explicitly relating it to the turbulence observed in transition dynamics of failed firms and we further assess how such instability associates with firm growth. We also investigate the relative performance of defaulting firms by comparing transition dynamics of the two groups. In more details, we now apply a methodology based on transition matrices.

In order to have a meaningful comparison, in each year, we define 5 states as the quintiles of the distribution of each variable. Such quintiles are defined within group ND and we examine how defaulting firms move around within these states. We make use of a variation of the metric $P^{\tau}_{\varphi,m}(X)$. We now consider the cumulative persistence index $CP^{\tau}_{\varphi,m}(X)$, for values of φ from $1-m$ to -1 we have:

$$CP^{\tau}_{\varphi,m,inf}(X) = \sum_{\varphi=1-m}^{-1} P^{\tau}_{\varphi,m}(X) \tag{4}$$

for $\varphi = 0$ we simply keep:

$$CP^{\tau}_{\varphi,m}(X) = P^{\tau}_{0,m,} \tag{5}$$

and for values of φ from 1 to m-1:

$$CP^{\tau}_{\varphi,m,sup}(X) = \sum_{\varphi=1}^{m-1} P^{\tau}_{\varphi,m}(X). \tag{6}$$

[7] See Pinches et al. (1973), Johnson (1978), Yli-Olli and Virtanen (1989).

[8] This is consistent with the previous evidence. See, for example, Beaver (1966), Dambolena and Khoury (1980), Bottazzi et al. (2011).

In Figures 4, 5 and 6 we can observe the cumulative persistence tents for the rates of growth of assets, sales and employees, respectively for group ND and group D. More in detail, one can appreciate the behavior of the CP index for different values of φ, thus, for value of $\varphi = 0$ on the abscissa, the ordinate reads the conditional probability of remaining in the quintile i at time t, given that you were in the same quintile at time t-τ. The ordinate at $\varphi = 1$ indicates the probability of moving upward by at least one class, whereas $\varphi = -1$ expresses the probability of falling down by at least one quintile, and so forth.

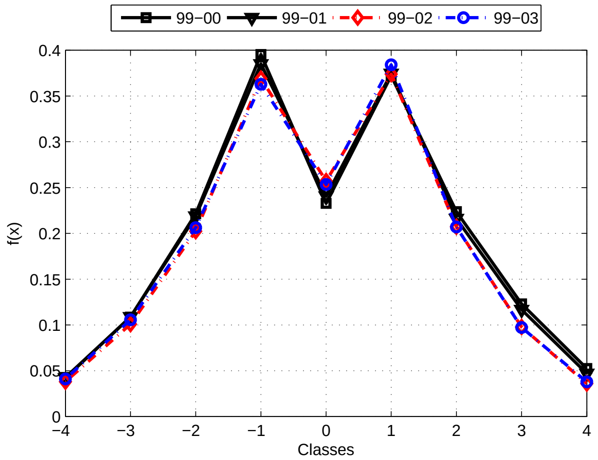
We also compute a different version of persistence index to take into account the fact that classes are not equally sized when applied to group D. Persistence tents based on the modified index are shown in the bottom panels of Figures 4, 5 and 6 for defaulting firms:[9]

$$P^{\tau}_{\varphi,m}(X)_{mod} = \frac{1}{\sum_{h=1}^{m}\sum_{l=1}^{m} n_{h,l}} \sum_{h=1}^{m} \sum_{l:l-h=\varphi} \hat{n}^{\tau}_{h,l} \tag{7}$$

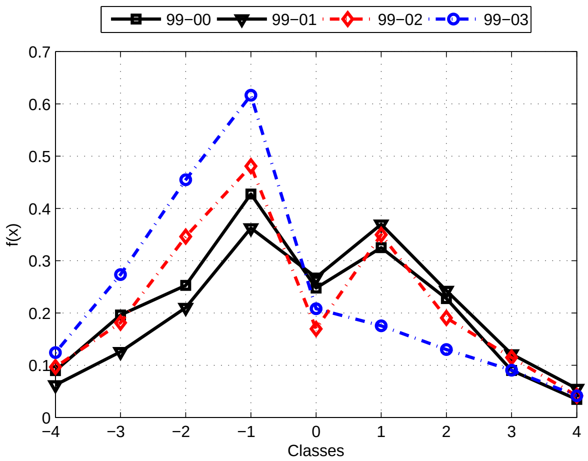
where $n_{h,l}$ is the absolute frequency, i.e., the total number of firms moving from state h at time t-τ to state l at time t. We overlay in the same plot the tents consistent with different τ-step transition. We start with the short-run transition from 1998 to 1999 and we gradually increase the time-span to 1998-2000, 1998-2001 up to 1998-2003. Results are shown in Figures 4, 5 and 6 for growth rates and in Figures 7, 8 and 9 for financial ratios.

[9] There is no need to add the tents for non-defaulting firms as in this case the two indexes yield the same result by construction.

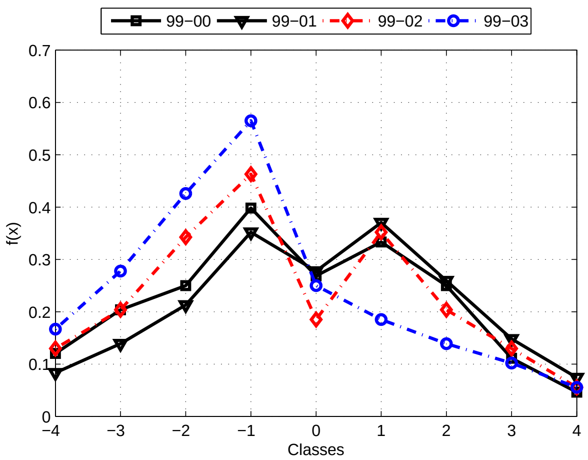
Fig. 4 Growth Rates: Cumulative Transition Probability Tents ($SALES_{GR}$)



Viable Firms: $CP^{\tau}_{\varphi,m}(X)$

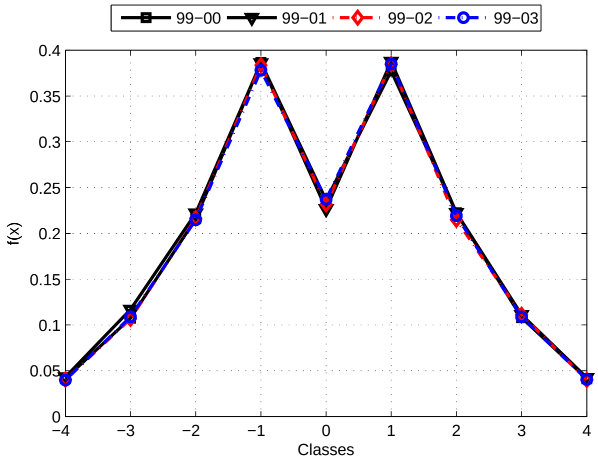


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)$

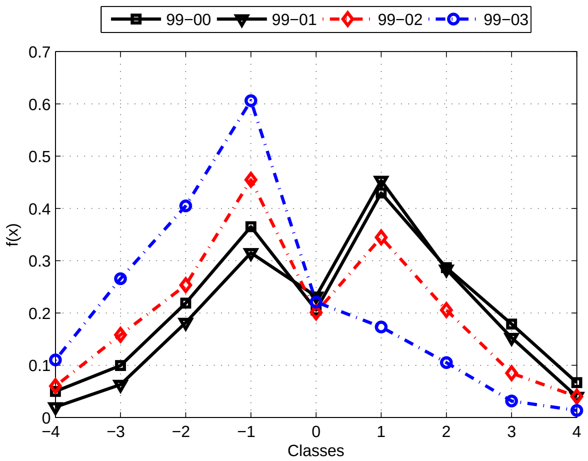


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)_{mod}$

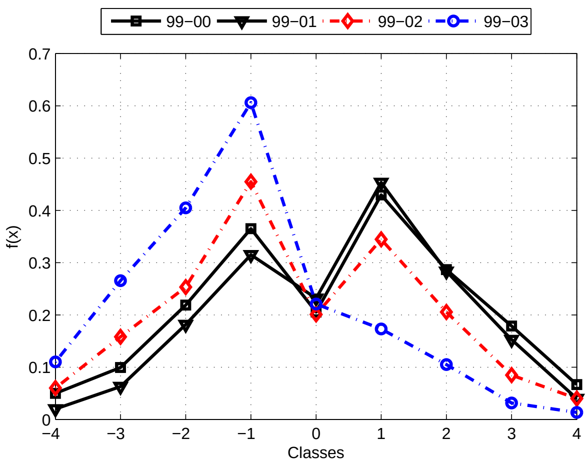
Fig. 5 Growth Rates: Cumulative Transition Probability Tents ($TOTALASSETS_{GR}$)



Viable Firms: $CP^{\tau}_{\varphi,m}(X)$

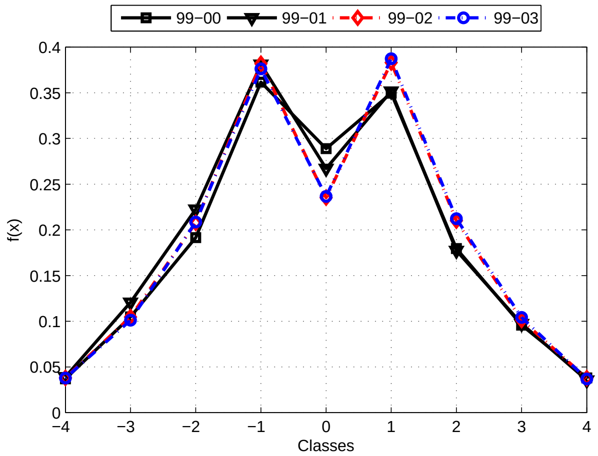


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)$

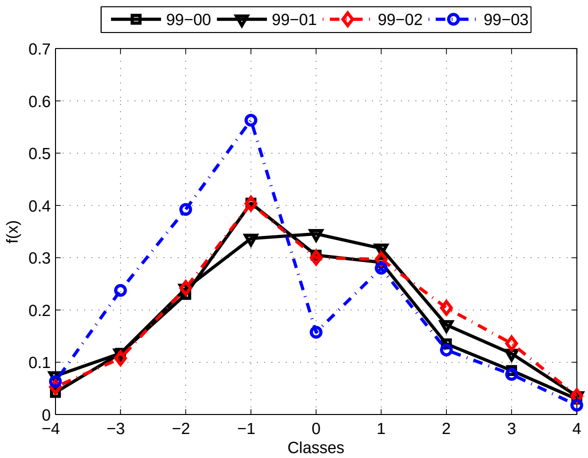


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)_{mod}$

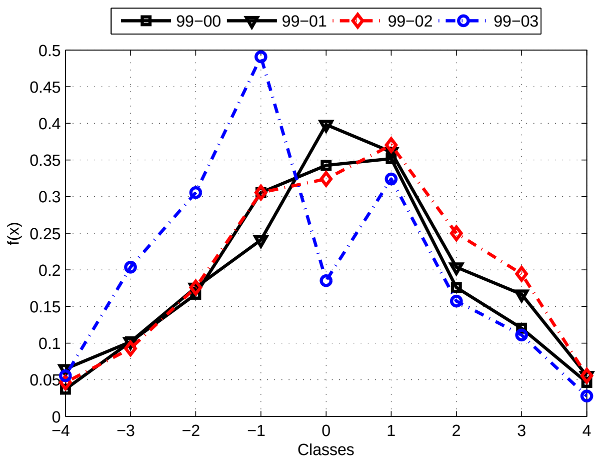
Fig. 6 Growth Rates: Cumulative Transition Probability Tents ($EMPLOYEES_{GR}$)



Viable Firms: $CP^{\tau}_{\varphi,m}(X)$



Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)$



Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)_{mod}$

It is worth noting that growth rates display relatively low persistence. Only about 25 percent of firms remain in the same quintile and this is true for both defaulting and non-defaulting firms. It is also interesting and quite surprising to note that, for the group of viable firms, the conditional probability of remaining in the same quintile does not change much as we increase the time span.[10]

Yet, it is clear that transition dynamics of defaulting firms are significantly different than those of viable firms. In group ND, transitions are symmetric and the probability of falling by at least one class down is almost identical to the probability of moving up by at least one quintile (around 0.4). In addition, for this group, there is a substantial overlapping of persistence tents relative to different τ time-spans.

In group D, persistence tents become increasingly unbalanced to the left with longer time-windows. Such tendency becomes particularly evident when we consider the 1999-2003 frame. The probability of having in 2003 a growth rate in a lower quintile than that observed in 1999 is as high as 0.6, whereas, the probability of improving is down to 0.2 or 0.3 in the case of employment growth. This is actually still quite high: about one third of defaulting firms performed better in 2003 than what they did in 1999. This proves that there substantial heterogeneity in growth rates dynamics and some firms still perform well (in relative terms) even in the year of default.

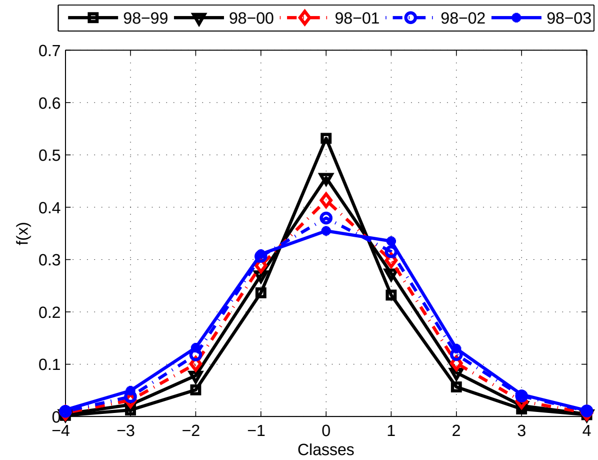
Moving to financial ratios, the following remarks can be made. First, there is evidence that financial structure is quite a stable entity, at least in viable firms. The degree of persistence is definitely higher than the one observed for growth rates. The stock variable is the most persistent as expected and as a matter of fact, it appears that is far more likely in the short run to remain in the same quintile (with a probability of 0.7) rather than moving either up or down. The persistence tents of group A flatten out as we increase the time span and yet the tendency to remain in the same class dominates all other larger scale movements. The tents for group B are surprisingly similar across the three ratios. In all, it appears that downward mobility is substantial: in fact, with probability of 0.7 the firm's position will deteriorate at least by one quintile. On the contrary, upward mobility is very low and in any case short-ranged. At most, we see that firms may move up by one quintile. It is also interesting to note that most mobility takes place in 2002 for COST, whereas for EQ we see that the probability of falling down leaps in 2003. The deterioration of operating profitability is more gradual.

It is also worth pointing put how such tents exhibit fat left tails (for EQ and ROS) and right tail for COST. In the last year, the probability of a sudden large-scale financial collapse is rather high, more than 0.1 for COST and EQ and almost up to 0.2 for ROS. This is saying that some firms that appeared to be financially sound (being in the top quintile of the distribution) up to one year prior to default experience a dramatic worsening of their financial status in the year of default.

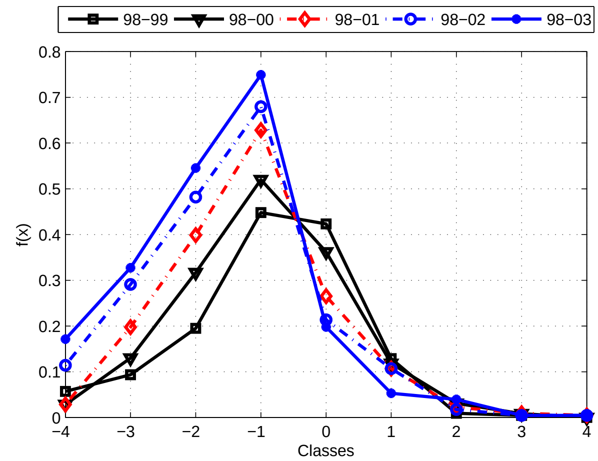
Most comments made here, apply to the new index 7, but minor qualifications are required. Results for growth rates are very similar to those reported here, whereas persistence tents for financial ratios are slightly different. The difference with respect to the viable firms case is still striking and positive skewness is rather evident. Yet the probability mass in the left tail of the tent is not as high. In fact the odds of remaining in the same quintile after six years remain as high as almost 0.4 and the probability of moving to a lower quintile is slightly higher than 0.5. Also it must be noted that the size of the long-ranged downward mobility is quite sensibly reduced: the probability of a 4-state leap down is now much lower and at best around 0.05 for EQ. Finally, the odds of improving at least by one-quintile are still as high as 10 percent for all the three variables.

[10] In more detail, one can see that only in the case of employees rate of growth such probability becomes smaller as the time-span become longer.

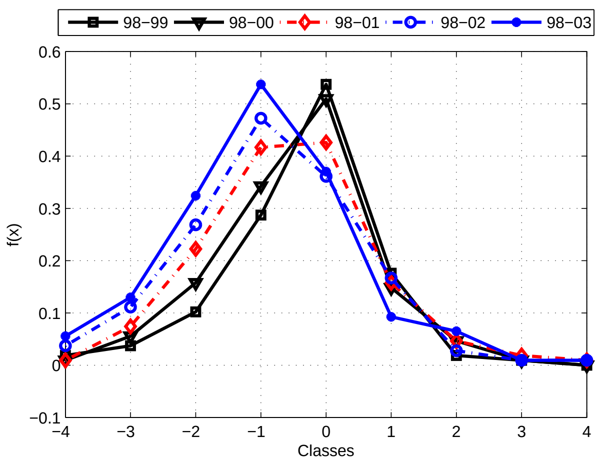
Fig. 7 Financial Ratios: Cumulative Transition Probability Tents (ROS)



Viable Firms: $CP^{\tau}_{\varphi,m}(X)$

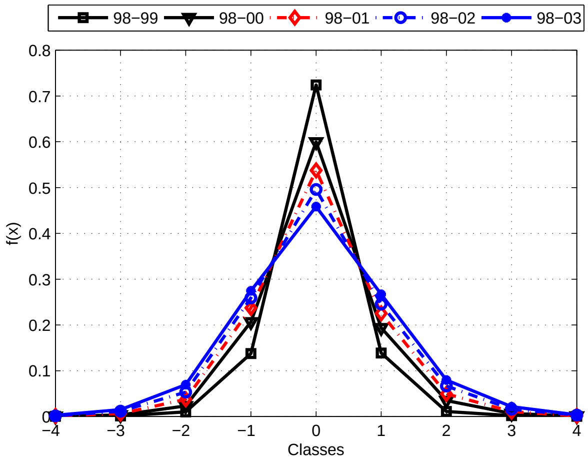


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)$

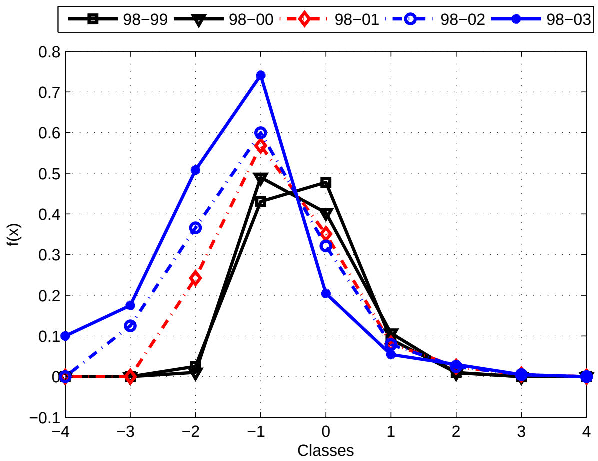


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)_{mod}$

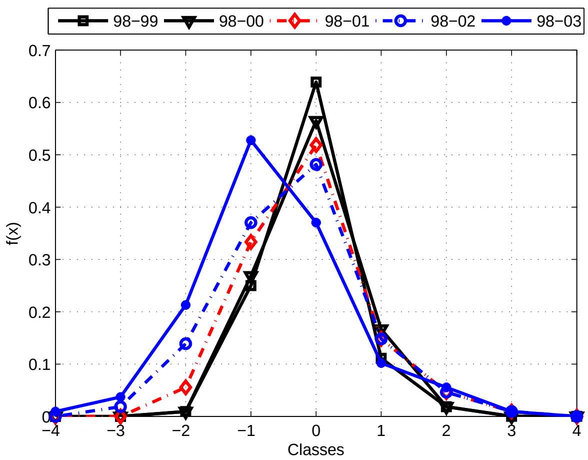
Fig. 8 Financial Ratios: Cumulative Transition Probability Tents (EQ)



Viable Firms: $CP^{\tau}_{\varphi,m}(X)$

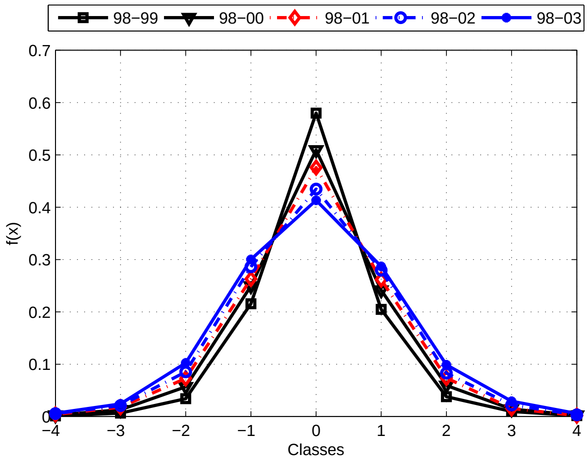


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)$

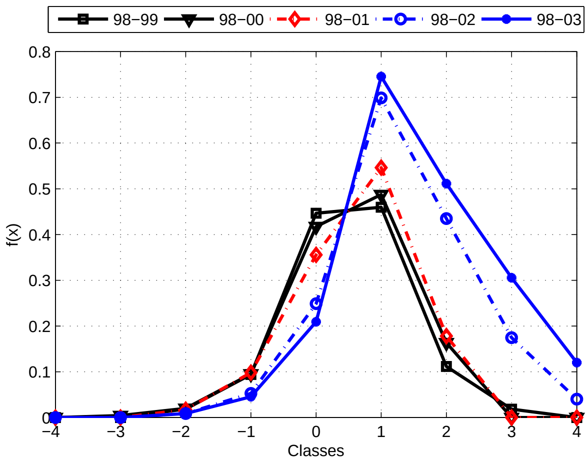


Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)_{mod}$

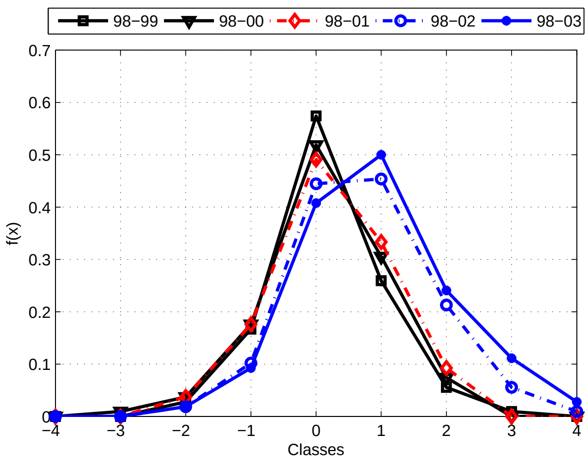
Fig. 9 Financial Ratios: Cumulative Transition Probability Tents (COST)



Viable Firms: $CP^{\tau}_{\varphi,m}(X)$



Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)$



Defaulting Firms: $CP^{\tau}_{\varphi,m}(X)_{mod}$

4 Analysis of Correlations

So far, we have been focusing on the analysis of a single dimension at a time. Now we move on to assess the co-movements of such variables. First, we look at the correlation over time of the financial structure, as a three dimensional object and then we evaluate of such structure associates with growth using a regression-based analysis. In Table 1 one can appreciate in a pairwise fashion how the correlation between the three financial variables evolves over time. To complement the picture, we also show in Table 2 the correlation and partial correlation matrix for different years.

We observe positive correlation between financial pressure and debt exposure and this dramatically increases in the year of default. Financial solidity and operating profitability do not appear to be much correlated up to one year prior to failure but becomes heavily intertwined in the last year of survival. Operating profitability and financial pressure are positively correlated quite surprisingly but they appear to be negatively associated in 2003. yet such correlation is weak as the partial correlation is not significant and seems to be driven by the strong positive (negative) correlation of EQ with ROS and EQ with COST. From Table 1, it interesting to note that the clouds of points appear relatively stable up to 2001 and in 2002 most movements are driven by a falling operating profitability, whereas a significant increase in financial pressure and financial fragility becomes apparent only in 2003.

We proceed as follows. The idea here is to assess the relationship between the financial status and growth. In more detail, we want to investigate the degree to which the well-documented progressive deterioration of financial conditions hampers growth, and the extent to which this effect changes over time. Our ex-ante guess is that this worsening of the financial status should become more and more binding over time. In order to check this hypothesis, we perform a very simple, yet informative exercise. First, as a rough approximation, we look at the correlation over time between rates of growth and financial ratios and results are shown in Table 1.

Even in this case, it is striking how the strength of the correlation between financial structure and growth increases in the last year.

This is true regardless the proxy used to measure growth but it is certainly stronger for assets growth. Indeed, we see the financial pressure is significantly negatively associated with the growth of total assets in 2003, whilst this is not so for sales and employees. It is also worth pointing out that the deterioration of profitability in 2002 matches with a positive significant correlation between profitability and growth in the same year. This could possibly be interpreted as evidence of financial constraints. The correlation between profitability and growth becomes even stronger in the year of default, following a further worsening in firms profitability. Financial solvency, as measured by EQ, is mostly negatively correlated with growth, even though this is not significant. Yet, in 2003 it becomes strongly positive and again provides some support to the idea that financial fragility matters.

We now test more accurately these evidence by means of regression analysis.

5 Regression Analysis

Rather than simply run a pooled regression, we opt for a time-varying coefficients model that boils down to evaluating the model separately for each year. In this way, we do not only allow for a intercept change over time, which is what is normally captured by the time dummies in a pooled model, but also for a change in the slope. Formally the model takes the following form:

$$GR_{i,t} = \beta_{0,t} + \beta_{1,t} EQ_{i,t} + \beta_{2,t} ROS_{i,t} + \beta_{3,t} COST_{i,t} + \eta_{i,t} \tag{8}$$

and it is separately estimated for $t = 1999, .., 2003$, where $GR_{i,t}$ stands for the rate of growth of assets.

Results are shown in Table 3. As it appears from the correlations that growth of total assets is the most responsive variable, we focus on this now. Results on sales and employees are presented in Appendix and discussed at the end of this section.

The trend observed in the sign of the regression coefficients confirms the picture from the correlation matrix. First, EQ is mostly negatively associated (even if significant only in 2000), but the coefficient

Table 1 Pairwise Correlation and Partial Correlation Matrix

	EQ	ROS
1998		
EQ		
ROS	0.1560 [0.1451]	
COST	-0.2905*** [-0.2852***]	-0.0600 [-0.0155]
1999		
EQ		
ROS	0.0643 [0.0230]	
COST	-0.3182*** [-0.3131***]	0.1341*** [-0.1201]
2000		
EQ		
ROS	-0.1052 [0.0230]	
COST	-0.1905 [-0.1701*]	0.2573*** [0.2430**]
2001		
EQ		
ROS	-0.1187 [-0.0934]	
COST	-0.0936 [-0.0581]	0.3300*** [0.3226***]
2002		
EQ		
ROS	0.1465 [0.1691*]	
COST	-0.1993** [-0.2161**]	0.0929 [0.1260]
2003		
EQ		
ROS	0.6105*** [0.5261***]	
COST	-0.5044*** [-0.3735***]	-0.3759***[-0.0994]

*p<0.1, **p<0.05, ***p<0.01.
Partial correlations are in squared brackets

Table 2 Contemporaneous Spearman's rank correlation coefficients

ASSETS_GR	1999	2000	2001	2002	2003
EQ	-0.1217	-0.2417	-0.1400	0.0917	0.5909***
ROS	0.1572	-0.1056	-0.0224	0.2825***	0.5467***
COST	-0.1829	0.1416	-0.2730***	-0.1981	-0.5204***
SALES_GR	1999	2000	2001	2002	2003
EQ	-0.1623	-0.2041	-0.0917	0.0502	0.3125***
ROS	0.1572***	0.2351	-0.0218	0.3659***	0.4111***
COST	-0.0191	0.1571*	-0.1106	-0.0308	-0.1220
EMP_GR	1999	2000	2001	2002	2003
EQ	-0.0402	-0.2414	-0.1618	-0.0566	0.2493***
ROS	03034***	0.0716	0.0421	0.2319	0.3676***
COST	-0.2904***	-0.0289	-0.0034	0.0492	-0.1138

Significance levels: *** : 1%

becomes positive and significant in 2003. The impact of ROS is in general positive and the coefficient spikes up in 2002, again confirming the trend in the correlation coefficient. Yet in 2003, the regression coefficient is lower than in 2003 and this suggest that the high correlation is spurious and driven by the effect of other variables, most likely the EQ ratio.[11] At last, financial pressure appears as expected to be always negatively correlated with growth.

The striking result from this regression exercise is the trend on the R squared. The explanatory power of the model in 1999 is in line with the typical performance of firm-growth regression (see Coad, 2010a, for an example). Most growth models in industrial dynamics typically exhibit relatively low explanatory power. As we move closer the the date of default though, the fit of the model improves substantially and goes up to 52.7 percent in 2003. This is a quite relevant results as it confirms that dynamics in financial structure (as a multivariate entity) and growth become much more intertwined as the firm approaches the event of default. A possibly even more interesting exercise is to disentangle the extent to which each independent variable contributes to the overall explanatory power. Following Maddala (2001), the coefficient of multiple determination of the multivariate regression $R^2_{y,x1,x2,x3}$ can be decomposed as follows:

$$R^2_{y,x1,x2,x3} = \beta_1 \frac{S_{x1,y}}{S_{y,y}} + \beta_2 \frac{S_{x2,y}}{S_{y,y}} + \beta_3 \frac{S_{x3,y}}{S_{y,y}} \tag{9}$$

and we shall define the partial R2s in Table 3 respectively as:

$$R^2_{EQ} = \frac{\beta_1 \frac{S_{x1,y}}{S_{y,y}}}{R^2_{y,x1,x2,x3}} \tag{10}$$

$$R^2_{ROS} = \frac{\beta_2 \frac{S_{x2,y}}{S_{y,y}}}{R^2_{y,x1,x2,x3}} \tag{11}$$

$$R^2_{COST} = \frac{\beta_3 \frac{S_{x3,y}}{S_{y,y}}}{R^2_{y,x1,x2,x3}}. \tag{12}$$

The partial $\mathrm{R}^2 arereportedinparentheses, whilsttheplainnumbersarerespectively \beta_1 \frac{S_{x1,y}}{S_{y,y}}$, $\beta_2 \frac{S_{x2,y}}{S_{y,y}}$ and $\beta_3 \frac{S_{x3,y}}{S_{y,y}}$ and provide the explanatory power of each regressor relative to the total variance of the model. As expected, the drop in operating profitability has a heavy weight (16 percent) in 2002, whereas in the last year, negative (or the lack of) net-worth appears to be the most influencing variable with a 23 percent. Financial pressure also plays a rather important role with 18 percent.

In order to control for outliers, we also run a robust regression that attaches low weights to those observations with high leverage.[12] We also use least absolute deviation (LAD) estimators to control for extreme observations.[13] Both methods are to be considered more reliable than simple OLS when applied to rates of growth, whose distribution is known to be heavy-tailed. Estimates are shown in Table 12 in the Appendix and both regressions confirm the OLS findings.

The year-by-year estimates reveal that regressions coefficient are not constant over time. In order to assess how significant these movements are, we estimate the following pooled model in which we let each time dummy interact with each financial ratio. Formally, the model can be written as follows:

$$\begin{aligned} GR_{i,t} = {} & \beta_0 + \beta_1 EQ_{i,t} + \beta_2 ROS_{i,t} + \beta_3 COST_{i,t} + \beta_4 D_{00} + \beta_5 D_{01} \\ & + \beta_6 D_{02} + \beta_7 D_{03} + \beta_8 D_{00} * EQ_{i,t} + \beta_9 D_{01} * EQ_{i,t} \\ & + \beta_{10} D_{02} * EQ_{i,t} + \beta_{11} D_{03} * EQ_{i,t} + \beta_{12} D_{00} * ROS_{i,t} \\ & + \beta_{13} D_{01} * ROS_{i,t} + \beta_{14} D_{02} * ROS_{i,t} + \beta_{15} D_{03} * ROS_{i,t} \\ & + \beta_{16} D_{00} * COST_{i,t} + \beta_{18} D_{01} * COST_{i,t} + \beta_{19} D_{02} * COST_{i,t} \\ & + \beta_{20} D_{03} * COST_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{13}$$

[11] This is also consistent with the not-displayed partial correlation with growth.

[12] See Berk (1990), Goodall (1983), and Rousseeuw and Leroy (1987) for an overview of the method, and Hamilton (1991) for a detailed description of the STATA command.

[13] LAD regressions are thought to perform better than standard OLS when residuals are not Gaussian. See Bottazzi et al.(2008), Coad (2010a) for others applications of the LAD regression.

Table 3 Dependent Variable: Assets Growth (1)

Years	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$EQ_{i,t}$	-0.258	-0.638***	-0.279	0.071	0.385***
	(0.180)	(0.235)	(0.186)	(0.164)	(0.094)
$ROS_{i,t}$	0.696**	-0.209	0.245	0.923***	0.348**
	(0.271)	(0.381)	(0.337)	(0.187)	(0.143)
$COST_{i,t}$	-2.840**	-1.784	-3.715***	-2.824**	-2.900***
	(1.318)	(1.518)	(1.198)	(1.151)	(0.704)
N	108	108	108	108	108
Adj R2	0.086	0.047	0.073	0.205	0.527
R2	0.112	0.074	0.099	0.227	0.540
$R2_{EQ}$	0.79%	6.15%	1.71%	0.57%	23.58%
	(7.03%)	(83.06%)	(17.31) %	(2.50%)	(44.75%)
$R2_{ROS}$	6.19%	0.31%	-0.12%	16.35%	11.29%
	(55.30%)	(4.16%)	(-1.17%)	(79.77%)	(20.91 %)
$R2_{COST}$	4.22%	0.94%	8.30%	4.02%	18.10 %
	(37.67%)	(12.78%)	(83.87%)	(17.72%)	(34.34 %)

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

This specification allows us to test whether the difference across five years is significant, and regression results are shown in Table 4. As before, we also show in column 3, the estimates obtained with robust regression methods in order to control for outliers.

We can use a simple F-test under the null hypothesis that for each ratio, all the interaction terms are zero. We performed the test on the robust regression estimates and The F-test value for the EQ interaction terms is 12.83 (7.66 on the OLS) and thus rejects the null at 1 percent level, 2.51 (2.57 on the OLS) for ROS interaction terms, thus we reject at 5 percent but not at 1 percent, whereas we are not able to reject the null for COST interactions terms with an F statistics of 1.20 (0.28 on the OLS). This is telling us that the observed variation in regression coefficients over time is statistically significant for EQ and to some extent for ROS. The sign-switching of the coefficient attached to EQ in 2003 is clearly the main force driving this time-variation.

Unobserved heterogeneity is a possible issue in panels and we control for it with fixed effects. Yet, the F-test on the joint significance of the individual effects does not reject the null and this suggests that there is no substantial unobserved heterogeneity. Quite likely, we are already implicitly controlling for unobserved heterogeneity by focusing on defaulting firms.

The use of more sophisticated techniques such as GMM is limited by the small size of the sample and mostly by the clear non-stationarity of financial ratios for defaulting firms. This prevents the use of lagged variables both in the original specification and as instruments for contemporaneous variables.

At last, we explicitly compare the performance of defaulting firms with that of viable firms. We do so by introducing a dummy variable D_{def} that takes value 0 if the firm is viable, and 1 when the firm belongs to the defaulting group. We also let this dummy interact with all the financial ratio and this allows us to assess whether financial structure affects differently defaulting firms. The model specification is as follows:

$$\begin{aligned} GR_{i,t} = \beta_0 + \beta_1 EQ_i + \beta_2 ROS_i + \\ \beta_3 COST_i + \beta_4 D_{def} + \beta_5 D_{def} * EQ_i + \\ \beta_6 D_{def} * ROS_i + \beta_7 D_{def} * COST_i + \nu_i \end{aligned} \tag{14}$$

$\forall\, t = 1999:2003.$

Results are shown in Table 5 and are consistent with the robust estimation displayed in Table 13 in the Appendix.

There is evidence that the growth process of defaulting firms responds differently to financial structure than that of surviving firms. This suggests that the nexus between growth and finance is non-linear. First

Table 4 Dependent Variable: Assets Growth (2)

	(1) Model I-OLS	(2) Model II-OLS	(3) Robust Regression
$EQ_{i,t}$	0.099	-0.258	-0.288*
	(0.065)	(0.181)	(0.156)
$ROS_{i,t}$	0.599***	0.696**	0.536**
	(0.095)	(0.272)	(0.234)
$COST_{i,t}$	-3.162***	-2.840**	-1.566
	(0.475)	(1.320)	(1.137)
D_{00}	0.078***	0.167**	0.170**
	(0.025)	(0.082)	(0.071)
D_{01}	0.022	0.082	0.117*
	(0.025)	(0.082)	(0.070)
D_{02}	-0.032	-0.084	-0.067
	(0.025)	(0.083)	(0.072)
D_{03}	-0.117***	-0.167**	-0.210***
	(0.028)	(0.068)	(0.059)
$D_{00} * EQ_{i,t}$		-0.380	-0.287
		(0.271)	(0.233)
$D_{01} * EQ_{i,t}$		-0.021	-0.055
		(0.270)	(0.233)
$D_{02} * EQ_{i,t}$		0.329	0.281
		(0.266)	(0.229)
$D_{03} * EQ_{i,t}$		0.643***	0.765***
		(0.202)	(0.174)
$D_{00} * ROS_{i,t}$		-0.905**	-0.495
		(0.425)	(0.366)
$D_{01} * ROS_{i,t}$		-0.451	-0.298
		(0.454)	(0.391)
$D_{02} * ROS_{i,t}$		0.228	0.369
		(0.351)	(0.303)
$D_{03} * ROS_{i,t}$		-0.348	-0.249
		(0.304)	(0.262)
$D_{00} * COST_{i,t}$		1.056	-0.966
		(1.855)	(1.598)
$D_{01} * COST_{i,t}$		-0.875	-2.403
		(1.847)	(1.592)
$D_{02} * COST_{i,t}$		0.017	-0.883
		(1.902)	(1.639)
$D_{03} * COST_{i,t}$		-0.059	0.192
		(1.484)	(1.278)
N	540	540	540
Adjusted R2	0.395	0.427	0.471

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

we see that the dummy variable signalling default is significant and in 2003 is, as expected, negatively correlated with growth. Yet, we must note how belonging to defaulting firms positively associates with growth in 2000 and 2001. This confirms that such firms are still performing relatively well up until two years prior to default. Once more, we find little evidence of a real (as opposed to financial) shadow of death.

As expected, financial fragility measured by EQ again appears as a key factor hampering growth of defaulting firms in 2003, and the sign of the coefficient attached to this variable switches from negative to positive. Operating liquidity and growth are again more strongly correlated in the year prior to failure for defaulting firms. Quite surprisingly, there is no evidence that financial pressure is affecting more defaulting firms than non-defaulting firms.

Now we turn to alternative measures of growth based on sales and employees and results are shown in Tables 6 and 7. The sign-switching of the coefficient attached to EQ is evident for both sales and employees growth. liquidity is again more strongly associated with sales growth in the year prior to default

Table 5 Dependent Variable: Assets growth (3)

	(1)	(2)	(3)	(4)	(5)
Years	1999	2000	2001	2002	2003
$EQ_{i,t}$	-0.239***	-0.112***	-0.216***	-0.190***	-0.118***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
$ROS_{i,t}$	0.158***	0.178***	0.095***	0.239***	0.130***
	(0.020)	(0.022)	(0.021)	(0.021)	(0.021)
$COST_{i,t}$	-2.726***	-1.822***	-2.642***	-3.110***	-2.449***
	(0.122)	(0.124)	(0.122)	(0.143)	(0.137)
D_{def}	-0.018	0.146**	0.089*	-0.067	-0.095***
	(0.057)	(0.058)	(0.052)	(0.056)	(0.034)
$D_{def} * EQ_{i,t}$	-0.019	-0.526***	-0.064	0.262	0.502***
	(0.175)	(0.203)	(0.185)	(0.185)	(0.090)
$D_{def} * ROS_{i,t}$	0.538**	-0.387	0.150	0.684***	0.218
	(0.263)	(0.330)	(0.336)	(0.213)	(0.137)
$D_{def} * COST_{i,t}$	-0.114	0.037	-1.073	0.286	-0.450
	(1.279)	(1.317)	(1.197)	(1.308)	(0.680)
N	10059	10063	10065	10063	10068
R-squared	0.065	0.028	0.056	0.063	0.061
A R-Squared	0.065	0.028	0.055	0.062	0.060

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

but does not appear as significant in the last year. Our interpretation is that financially distressed firms are no longer sensitive to (or the lack thereof) liquidity. Financial conditions are so severe that an increase in liquidity would not favor growth. Interestingly enough, financial pressure (proxied by COST) enters the regression with a positive coefficient in the sales growth model and with a negative one for employment growth. We find a first evidence that financial structure may not have an homogenous effect on growth, irrespectively of the proxy of size used. Actually this suggests that financial pressure has indeed a different impact. Employment appears to be the most sensitive to increasing financial charges. Yet, we observe that financial pressure positively associates with sales growth in 2003. One could explain this by saying that higher interest payments elicit a positive effect on the efficiency of the firm because it put more pressure on employees. This translates into higher sales growth but the financial distress refrains the firm from also expanding assets. This result tells us that in principles the growth of each firm's dimension may respond differently to the same financial shock. This may be the case even more for distressed firms, for which trade-offs between different growth rates are more likely to arise.

5.1 Shocks-based Regressions

In section 3 we provided evidence of substantial turbulence measured via the metrics $CP^{\tau}_{\varphi,m,inf}(X)$. In order to fully capture the effect of such dynamics in a regression exercise, we replace levels of financial ratios with shocks computed as the first difference of such ratios and we re-run regressions 8 13 and 14. In each period t, we define each shock δ as follows:

$$\delta^{EQ}_{i,t} = EQ_{i,t} - EQ_{i,t-1} \tag{15}$$

$$\delta^{ROS}_{i,t} = ROS_{i,t} - ROS_{i,t-1} \tag{16}$$

$$\delta^{COST}_{i,t} = COST_{i,t} - COST_{i,t-1}. \tag{17}$$

The results of the new shocks-based regression are displayed in Table 8, 9 and 10 and they confirm the findings documented in the previous section. Yet, by comparing Table 8 with Table 4, one can appreciate how the fit of the model improves and how such improvement is proportional to the time-distance to default.

Table 6 Dependent Variable: Sales Growth

	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$EQ_{i,t}$	-0.219***	-0.173***	-0.173***	-0.215***	-0.157***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
$ROS_{i,t}$	0.413***	0.418***	0.396***	0.555***	0.647***
	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)
$COST_{i,t}$	-0.926***	-0.424***	-0.999***	-1.580***	-1.554***
	(0.133)	(0.126)	(0.131)	(0.148)	(0.152)
D_{def}	-0.064	-0.034	0.057	-0.021	-0.202***
	(0.062)	(0.059)	(0.056)	(0.058)	(0.037)
$D_{def} * EQ_{i,t}$	0.054	-0.435**	-0.155	0.116	0.265***
	(0.190)	(0.208)	(0.199)	(0.192)	(0.100)
$D_{def} * ROS_{i,t}$	0.620**	0.708**	0.113	0.591***	0.117
	(0.286)	(0.337)	(0.360)	(0.220)	(0.152)
$D_{def} * COST_{i,t}$	0.097	0.330	-1.084	-0.765	2.761***
	(1.394)	(1.347)	(1.283)	(1.354)	(0.754)
N	10059.000	10063.000	10065.000	10063.000	10068.000
R-squared	0.051	0.042	0.042	0.080	0.099
A R-Squared	0.050	0.041	0.041	0.079	0.099

*p<0.1, **p<0.05, ***p<0.01.
Standard errors in parentheses, clustered by individual.

Table 7 Dependent Variable: Employment Growth

	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$EQ_{i,t}$	-0.132***	-0.059***	-0.093***	-0.088***	-0.050***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.013)
$ROS_{i,t}$	0.195***	0.183***	0.175***	0.178***	0.331***
	(0.020)	(0.021)	(0.022)	(0.023)	(0.025)
$COST_{i,t}$	-0.592***	-0.437***	-0.849***	-0.813***	-0.812***
	(0.122)	(0.117)	(0.132)	(0.152)	(0.163)
D_{def}	-0.029	0.092*	0.030	-0.004	0.054
	(0.057)	(0.055)	(0.056)	(0.060)	(0.040)
$D_{def} * EQ_{i,t}$	0.118	-0.272	-0.299	-0.124	0.238**
	(0.174)	(0.192)	(0.200)	(0.197)	(0.107)
$D_{def} * ROS_{i,t}$	0.643**	-0.193	0.163	0.189	-0.165
	(0.262)	(0.312)	(0.361)	(0.226)	(0.164)
$D_{def} * COST_{i,t}$	-1.529	-1.306	0.288	-0.377	-2.653***
	(1.278)	(1.245)	(1.289)	(1.393)	(0.812)
N	10059	10063	10065	10063	10068
R-squared	0.019	0.009	0.012	0.011	0.031
A R-Squared	0.018	0.009	0.011	0.010	0.030

*p<0.1, **p<0.05, ***p<0.01.
Standard errors in parentheses, clustered by individual.

One possible explanation for this is that the correlation between the shocks and their level (shown in Table 11) increases as we move closer to the default event.[14] In 2003 shocks are well instrumented by levels, but this does not work equally well 5 years to default. This may suggest that this latter specification shall be preferred to the simple level equation.

[14] We also check correlations between shocks and levels using the sample of non-failed firms and such correlations are stable over time and smaller than that exhibited by failed firms.

Table 8 Dependent Variable: Assets Growth (4)

Years	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$\delta_{i,t}^{EQ}$	-0.931***	-0.394	-0.774***	-0.235	0.371***
	(0.332)	(0.324)	(0.290)	(0.239)	(0.104)
$\delta_{i,t}^{ROS}$	0.146	-0.250	0.624*	1.095***	0.247*
	(0.350)	(0.375)	(0.368)	(0.220)	(0.142)
$\delta_{i,t}^{COST}$	-5.507***	-11.269***	-6.275***	-6.623***	-4.126***
	(1.509)	(2.182)	(1.614)	(1.540)	(0.843)
N	108.000	108.000	108.000	108.000	108.000
R-squared	0.189	0.213	0.183	0.305	0.548
A R-Squared	0.165	0.190	0.159	0.285	0.535

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

6 Final Remarks

In this paper we characterize patterns observed for defaulting firms *vis-à-vis* non-failed firms along three dimensions: long-run solvency, profitability and financial pressure. Results suggest that defaulting firms appear to be structurally weaker than viable firms. Such weaknesses is well documented by both the profile analysis and the turbulence found in the failing firms' transition dynamics.

The evidence gathered in this work suggests that default dynamics unfold relatively quickly. Defaulting firms are on average more financially fragile firms already, and the shadow of death is detectable even 5 years prior to default in financial structure. Yet, this weakness does not have a contemporaneous negative knock-on effect on growth. Indeed, the average failing firm is performing in terms of growth rates as well as the viable firms up to to 2001.

A tentative explanation would be that such firms survive until a negative (demand) shock hit them, and when that happens, both their financial and productive apparatus break down. What matters for growth is first a sharp decline in operating profitability in the year prior to default and net-worth plummets in the year of default.

There is little evidence instead that financial pressure curtails growth defaulting firms to a greater extent. As a matter of fact, financial pressure exerts a negative effect on growth, but the impact is constant over time and this effect does not appear to be stronger for failing firms. This is true when we consider the growth of total assets. For sales and employment financial pressure (though higher) has a different effect. We observe that in the last year sales growth is actually positively affected by the increasing financial pressure, whereas the latter one elicits a negative effect on employment growth. This suggests that the three growth rates do not always move together in the same direction and they may respond differently to the same financial shock. If this was the case, a trade-off may possibly arise and this may become more stronger in a situation of distress, as in our case, or more generally during a recession phase. There is much room for further research here. The extent to which the patterns of different growth rates differ is still largely unexplored and we need to improve our understanding of co-movements of different growth rates. Future efforts should also be made to go beyond the average firm story. As of yet, our understanding of the dynamic processes that can lead to default is fairly limited and the characterization of heterogenous default patterns is the the next step ahead in our research agenda.

Table 9 Dependent Variable: Assets Growth (5)

	(1) OLS	(2) OLS	(3) Robust Regression
$\delta_{i,t}^{EQ}$	0.092	-0.931***	-1.451***
	(0.080)	(0.331)	(0.287)
$\delta_{i,t}^{ROS}$	0.384***	0.146	0.304
	(0.105)	(0.349)	(0.302)
$\delta_{i,t}^{COST}$	-5.946***	-5.507***	-3.976***
	(0.587)	(1.506)	(1.305)
D_{00}	0.111***	0.134***	0.114***
	(0.024)	(0.026)	(0.022)
D_{01}	0.048*	0.063**	0.060***
	(0.024)	(0.026)	(0.023)
D_{02}	-0.034	-0.007	-0.017
	(0.024)	(0.026)	(0.023)
D_{03}	-0.129***	-0.104***	-0.106***
	(0.026)	(0.028)	(0.024)
$D_{00} * \delta_{i,t}^{EQ}$		0.537	1.854***
		(0.439)	(0.380)
$D_{01} * \delta_{i,t}^{EQ}$		0.157	0.761*
		(0.455)	(0.395)
$D_{02} * \delta_{i,t}^{EQ}$		0.696	1.301***
		(0.438)	(0.379)
$D_{03} * \delta_{i,t}^{EQ}$		1.303***	1.972***
		(0.345)	(0.299)
$D_{00} * \delta_{i,t}^{ROS}$		-0.396	-0.874**
		(0.482)	(0.418)
$D_{01} * \delta_{i,t}^{ROS}$		0.478	0.299
		(0.529)	(0.458)
$D_{02} * \delta_{i,t}^{ROS}$		0.949**	0.584
		(0.437)	(0.379)
$D_{03} * \delta_{i,t}^{ROS}$		0.101	-0.148
		(0.373)	(0.323)
$D_{00} * \delta_{i,t}^{COST}$		-5.762**	-4.436**
		(2.454)	(2.126)
$D_{01} * \delta_{i,t}^{COST}$		-0.768	-3.493*
		(2.303)	(1.995)
$D_{02} * \delta_{i,t}^{COST}$		-1.116	-2.526
		(2.379)	(2.062)
$D_{03} * \delta_{i,t}^{COST}$		1.381	1.742
		(1.696)	(1.470)
N	540	540	540
R-squared	0.448	0.498	0.545
A R-Squared	0.441	0.480	0.528

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

Table 10 Dependent Variable: Assets Growth (6)

Years	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$\delta_{i,t}^{EQ}$	-0.957***	-0.239***	-0.919***	-0.581***	-0.272***
	(0.029)	(0.028)	(0.026)	(0.025)	(0.023)
$\delta_{i,t}^{ROS}$	-0.129***	-0.467***	-0.050*	-0.125***	0.012
	(0.029)	(0.031)	(0.028)	(0.029)	(0.028)
$\delta_{i,t}^{COST}$	-2.897***	-2.260***	-3.995***	-3.479***	-4.581***
	(0.142)	(0.156)	(0.164)	(0.179)	(0.177)
D_{def}	-0.017	0.053***	0.058***	-0.001	-0.068***
	(0.019)	(0.017)	(0.016)	(0.018)	(0.020)
$D_{def} * \delta_{i,t}^{EQ}$	0.025	-0.155	0.144	0.346	0.643***
	(0.322)	(0.300)	(0.286)	(0.282)	(0.099)
$D_{def} * \delta_{i,t}^{ROS}$	0.275	0.217	0.674*	1.221***	0.236*
	(0.339)	(0.347)	(0.363)	(0.260)	(0.135)
$D_{def} * \delta_{i,t}^{COST}$	-2.610*	-9.009***	-2.279	-3.144*	0.455
	(1.466)	(2.018)	(1.596)	(1.820)	(0.805)
N	10056	10059	10063	10063	10062
R-squared	0.144	0.058	0.157	0.087	0.096
A R-Squared	0.143	0.058	0.156	0.086	0.095

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

Table 11 Correlation Structure over time

Years	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$Corr(\delta^{EQ}, EQ)$	0.2893***	0.0993	0.3048***	0.4491***	0.9350***
$Corr(\delta^{ROS}, ROS)$	0.3130***	0.2683***	0.3249***	0.7791***	0.8775***
$Corr(\delta^{COST}, COST)$	0.1566	0.3097***	0.3615***	0.2352**	0.8998***

**p<0.05, ***p<0.01.

7 Appendix

Table 12 Dependent Variable: Assets Growth

Robust Regression

Years	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$EQ_{i,t}$	-0.291**	-0.564***	-0.339*	-0.027	0.476***
	(0.141)	(0.185)	(0.179)	(0.161)	(0.084)
$ROS_{i,t}$	0.539**	0.018	0.242	0.900***	0.283**
	(0.212)	(0.300)	(0.323)	(0.184)	(0.124)
$ROS_{i,t}$	-1.457	-2.254*	-3.924***	-2.379**	-1.346**
	(1.030)	(1.194)	(1.150)	(1.130)	(0.660)

LAD Regression

Years	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003
$EQ_{i,t}$	-0.216	-0.560**	-0.195	-0.136	0.374***
	(0.179)	(0.250)	(0.258)	(0.147)	(0.109)
$ROS_{i,t}$	0.631**	-0.113	0.273	0.886***	0.354**
	(0.267)	(0.407)	(0.475)	(0.168)	(0.160)
$ROS_{i,t}$	-1.995	-2.336	-4.363**	-1.978*	-2.043**
	(1.273)	(1.655)	(1.677)	(1.049)	(0.817)

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

Table 13 Dependent Variable: Assets Growth

	(1)	(2)	(3)	(4)	(5)
Years	1999	2000	2001	2002	2003
			Robust Regression		
$EQ_{i,t}$	-0.205***	-0.123***	-0.188***	-0.157***	-0.111***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)
$ROS_{i,t}$	0.186***	0.226***	0.147***	0.250***	0.189***
	(0.016)	(0.019)	(0.017)	(0.018)	(0.016)
$COST_{i,t}$	-2.606***	-1.757***	-2.322***	-2.422***	-1.485***
	(0.101)	(0.105)	(0.103)	(0.119)	(0.106)
D_{def}	-0.020	0.145***	0.135***	-0.039	-0.140***
	(0.047)	(0.049)	(0.044)	(0.047)	(0.026)
$D_{def} * EQ_{i,t}$	-0.083	-0.450***	-0.159	0.133	0.588***
	(0.144)	(0.173)	(0.156)	(0.154)	(0.070)
$D_{def} * ROS_{i,t}$	0.356	-0.189	0.084	0.651***	0.088
	(0.217)	(0.280)	(0.283)	(0.177)	(0.106)
$D_{def} * COST_{i,t}$	1.178	-0.737	-1.710*	0.033	0.190
	(1.055)	(1.120)	(1.009)	(1.088)	(0.527)
			LAD Regression		
$EQ_{i,t}$	-0.203***	-0.129***	-0.177***	-0.157***	-0.112***
	(0.010)	(0.012)	(0.009)	(0.011)	(0.008)
$ROS_{i,t}$	0.197***	0.225***	0.144***	0.265***	0.173***
	(0.016)	(0.022)	(0.017)	(0.020)	(0.015)
$COST_{i,t}$	-2.647***	-1.751***	-2.165***	-2.442***	-1.669***
	(0.102)	(0.122)	(0.103)	(0.135)	(0.103)
D_{def}	-0.025	0.150***	0.114***	-0.030	-0.106***
	(0.046)	(0.056)	(0.043)	(0.053)	(0.025)
$D_{def} * EQ_{i,t}$	-0.014	-0.431**	-0.018	0.021	0.487***
	(0.144)	(0.192)	(0.152)	(0.172)	(0.067)
$D_{def} * ROS_{i,t}$	0.434**	-0.338	0.129	0.621***	0.181*
	(0.215)	(0.313)	(0.279)	(0.196)	(0.099)
$D_{def} * COST_{i,t}$	0.652	-0.585	-2.198**	0.464	-0.374
	(1.028)	(1.276)	(0.988)	(1.226)	(0.510)
N	10065	10065	10065	10065.000	10065

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