Debt and Financial Fragility: Italian Non-Financial Companies after the Pandemic

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December 2022

Abstract

This paper analyses the evolution of debt of Italian firms from 2010 to 2020 with special focus on the first year of the Covid-19 pandemic. By means of quantile regressions, our approach investigates several heterogeneities to assess the vulnerabilities of the most fragile firms. We find that, on average, Italian non-financial companies (NFCs) reduced their indebtedness over the sample period, a trend which did not get interrupted during the first year of the pandemic. By exploiting the high heterogeneity in the data, however, we find that the turmoil affected the most indebted firms and the trend of declining indebtedness for these firms was reversed. Moreover, sectors that were suspended *ex lege* during the first lockdown: i) already had the highest levels of the debt-to-assets ratios over our sample period, and ii) experienced the steepest increase in debt in 2020 relative to the previous year. Finally, our results show that highly indebted firms exhibit a qualitative different behaviour compared to the rest of the sample and that excessively piling up debt severely increases the likelihood of exiting the market.

Keywords: leverage; corporate debt; debt ratio; quantile regression

JEL codes: G30; G31; G32.

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Acknowledgements: We thank Hong Bo, Nicola Daniele Coniglio, Ciaran Driver, Jaideep Oberoi and Christine Oughton for the useful comments on earlier drafts of the paper.

1. Introduction

The corporate finance literature has long recognized that excessive piling up of corporate debt is negatively related to firms' performance, investment, and viability. Myers's (1977) seminal paper showed that debt overhang leads to under-investment by firms causing their value to contract. The negative relationship between overleveraging and investment is confirmed by several empirical contributions (see for instance Lang *et al.*, 1996; Hennessey 2004; Caldentey *et al.*, 2019; Kalemli-Özcan, *et al.*, 2022), and excessive debt accumulation is seen as one of the main factors leading to a firm's bankruptcy (Molina, 2005; Balcaen *et al.*, 2012). Even if the macroeconomic implications of corporate debt booms are still not entirely understood (Occhino and Pescatori, 2015; Brunnermeier and Krishnamurthy, 2020) and some scholars suggest that, given some conditions, they may be rather limited (Jorda *et al.*, 2020; Schularick, 2020), looking at firms' indebtedness becomes even more important in the wake of the multiple adverse shocks hitting the global economy.

Following the burst of the Covid-19 pandemic, governments around the world deployed a wide arsenal of tools to mitigate the effects of the shock, most of which aimed at easing firms' access to credit (Didier *et al.*, 2021). The need to react quickly and extensively to the turmoil implied a lax monitoring by borrowers and might have led to the exacerbation of existing distortions. Moreover, the pandemic hit while corporate leverage was already at an all-time high in some parts of the world, sustained by lax monetary policy, low interest rates and low credit spreads (Becket *et al.*, 2021). This calls for a closer examination of firms' leverage in the aftermath of the pandemic, as it also entails the soundness of the financial sector and the sustainability of public finances and support schemes in the coming years.

In this paper we analyse debt patterns of Italian firms from 2010 to 2020 by examining a very granular dataset on firms' balance sheets. Since we would miss relevant information by focusing only on the average firm, our approach consists of investigating several heterogeneities affecting the phenomenon under scrutiny and to assess the potential vulnerabilities of firms arising from the right tail of the distribution, which are the most exposed to negative shocks (Bernanke and Campbell, 1988). This is appropriate also in the wake of the shift to a tighter monetary policy by central banks around the world, since interest rate hikes though from low base, might increase the cost of debt and put some pressure on the sustainability of debt especially for such firms.

To preview our findings, quantile regressions enable us to establish that while, on average, Italian non-financial companies (NFCs) reduced their indebtedness during the first year of the pandemic, the turmoil especially affected the most highly indebted and fragile firms. Moreover, we find that sectors that were suspended *ex lege* during the first lockdown of the economy: i) already had the highest levels of the debt-to-assets ratios consistently through the sample period, and ii) they experienced the steepest increase in the average debt ratios in 2020 relative to the previous year.

Finally, our results show that highly indebted firms exhibit a qualitatively different behaviour compared to the rest of the sample. In particular, smaller firms and those with a lower share of tangible assets and slower growth prospects are potentially more exposed to large increases in the debt-to-assets ratios, especially during periods of financial distress. This might be the result of the Italian financial environment that provides few alternatives to debt. If raising funds via equity is only feasible for big and tangible-oriented players which are characterized by lower agency costs, smaller firms are first forced to resort to debt and then, if the latter excessively piles up, they are not able to switch to equity and find themselves in a sort of debt trap. The detrimental effects of excessive leverage are also confirmed when estimating the impact of such variable on the probability of firms' survival. We find that excessive indebtedness is a significant predictor of firms' closure.

The rest of the article proceeds as follows. In section 2 we discuss the institutional background of the Italian financial system and provide some stylized facts on firms' indebtedness during the pandemic. Section 3 investigates a number of heterogeneities characterizing the evolution of firms' debt over time. In section 4 we present some initial multivariate results on the determinants of leverage, while section 5 provides more detailed evidence coming from quantile regressions. In section 6 we focus on the consequences of excessive indebtedness and estimate its impact on firms' survival. Section 7 concludes.

2. The financial conditions of Italian NFCs

Strategies in terms of capital structure by Italian non-financial companies (NFCs) are severely constrained by both external and internal factors. Firms find resorting to equity very costly because of the lack of institutional investors, of government policies that have long incentivized households to invest in sovereign bonds in place of resorting to the equity market, and of a high degree of risk aversion by households. At the same time, Italian firms are typically small, opaque, and family-owned, and this prevents them from obtaining favourable financing conditions on the stock market (Carpenter and Rondi, 2006). In such setting, where also the private equity and venture capital markets are extremely thin, NFCs mostly resort to debt to satisfy their financing needs, relying especially on bank loans.

Apart from the traditional over-reliance on banks, Italian NFCs make intensive use of trade credit and have increasingly resorted to such instrument to compensate for the shortage of bank credit during the recent periods of financial turmoil (Ferrando and Mulier, 2013; Casey and O'Toole, 2014). The tightening conditions in the supply of bank loans and a number of policy interventions in the last decades have determined similar trends for other non-bank sources of debt, *e.g.* corporate bonds (Accornero *et al.*, 2018).[1]

[1] Consider for instance the introduction of so-called minibonds or the recent initiatives of Sace-Simest, part of the Cassa Depositi e Prestiti (the Italian investment bank) group aimed at increasing the resort to leasing and factoring.

The last few decades have been particularly challenging for the Italian economy. The country was hit by the Great Financial Crisis of 2008-2009 and by the European sovereign debt crisis (2010-2013). Moreover, its economy has experienced a progressive productivity slowdown. This has brought to light some patterns of credit misallocation during crises involving the rise of the so-called zombie firms, *i.e.* highly indebted and unprofitable firms which are still kept alive thanks to such credit distortions. The phenomenon has been extensively studied (Adalet McGowan *et al.*, 2018; Schivardi *et al.*, 2022) and is generally thought to have led to adverse consequences for the economy, even if it may be beneficial in the short-term to keep zombies alive (Schivardi *et al*., 2020).

In this context, the economic turmoil caused by the Covid-19 pandemic might have exacerbated such problems. In Figure 1 we plot the evolution of the mortality rate of Italian firms and the non-performing loans rate. Both measures show a decrease during the years of the pandemic. This clearly points to the effectiveness of the measures undertaken by the government to avoid mass default by domestic firms and alleviate the burden on households. Indeed, soon after the burst of the pandemic in Italy and the imposition of the lock-down, the Italian government launched the emergency packages "Cure Italy", "Liquidity" and "Relaunch Italy". These allowed for extensive public guaranteed loans to firms (financing backed by the Central Guarantee Fund for SMEs, under Article 13 of the 'Liquidity' decree law) and moratoria on existing loans for firms and households. Private sector initiatives extended the scope of the latter measures. As for the former, the government increased the guarantee ratio from 80% to 90% for loans of up to €5 million. Moreover, it introduced a 100% guarantee for loans below €30,000, requiring no fees from the borrower nor credit assessment by banks. Between March 2020 and the beginning of April 2022, the Guarantee Fund received 2,670,608 applications for a total amount of €239 billion (13% of total bank lending in 2021). 44 per cent of the requests regarded fully guaranteed loans below €30,000, for a total amount of €23 billion. More than 99 per cent of the total requests were accepted.[2]

Such initiatives were successful in limiting firms' distress. However, the need to quickly and extensively provide relief to NFCs and the limited screening of borrowers call for a closer examination of firm indebtedness in the aftermath of the pandemic.[3] This, apart from involving the competitiveness of the Italian production system and job security, will also entail the soundness of the domestic financial sector and the sustainability of public finances and the support packages in the coming years.

[Insert here Figure 1]

To this aim, we collect balance sheets information on Italian NFCs from Aida by Bureau Van Dijk (Bureau Van Dijk, 2021), see Appendix A for details. We select the debt to assets ratio as our variable of interest. In our granular dataset, consisting of 8,704,693 observations from 1,617,940 firms covering the period 2010-2020, Italian firms report an average debt to assets ratio of 0.7, ranging from 0 to 6.

Firms are characterized by high heterogeneity. Hence, we would lose relevant information by focusing only on the average value of the debt to assets ratio. To capture different patterns affecting the rest of the distribution, in Figure 2 we plot the evolution of different percentiles of the debt to assets ratio over time, alongside the mean.

[Insert here Figure 2]

A number of points are worth noticing. First, in spite of the numerous financial shocks hitting the country in the last decades, unexpectedly, debt to assets show, if anything, a

[2] See data from the joint Task Force on the monitoring of the liquidity measures by Ministero dell'Economia e delle Finanze, Ministero dello Sviluppo Economico, Bank of Italy, l'Associazione Bancaria Italiana (ABI), Mediocredito Centrale (MCC) and Sace, available at https://www.bancaditalia.it/focus/covid-19/task-force/index.html.

[3] Government measures, although necessary for the survival of firms during the hibernation of the economy, might be prone to allocative inefficiencies. The available evidence on the matter is mixed. Schivardi *et al.* (2020) show that the bulk of liquidity needs during the crisis comes from firms that were financially sound before the crisis, but Core and De Marco (2021) find that financially fragile firms were more likely to receive guaranteed loans.

slightly decreasing trend. This is true not only when considering the lowest percentiles of the distribution, but also when looking at the 75% percentile. This comes as a surprise, considering the rather cheap cost of credit in the Eurozone in the second part of the 2010s. It may have to do with the need of banks to consolidate their balance sheets markedly affected by non-performing loans until 2015, or with the prolonged economic stagnation that weakened credit demand by firms. Even if there is some evidence on the application of a more selective lending policy in the period under scrutiny (Bank of Italy, 2017), it seems that reduced profitability, investment opportunities and demand for credit by domestic firms played a major role (Accornero et al., 2017). Second, during the first year of the pandemic, 2020, on average Italian NFCs did not experience an increase in debt. Rather, they seemed to have reduced their indebtedness.

A different picture however emerges by the firms in the 95% percentile. Indeed, after peaking in 2015 it presents a decreasing trend that seems to be suddenly stopped by the pandemic. Hence, it seems that the Covid-19 turmoil has had its impact on the most highly indebted fragile firms. Figure 2 thus highlights the importance to closely look at the patterns characterizing various parts of the distribution of indebtedness. To provide a complete picture of firms' fragility and the impact of the pandemic, we investigate additional heterogeneities in the next section.

3. Evolution of debt

Figure 3a shows the changes in the mean debt-assets ratio in the North, the Centre, and the South (or the *Mezzogiorno*) of Italy[4]. In 2010 the average debt ratio was comparable across the three areas, with only a marginal higher value for the South. During the course of the following decade, however, debt fell markedly in the North but only to a lower extent in the

[4] The North includes the regions of Piedmont, Aosta Valley, Liguria, Lombardy, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, and Emilia-Romagna. The Centre comprises Tuscany, Marche, Umbria, and Lazio. The South includes Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, and Sardinia.

two other areas, thus contributing to widening the gap between the North and the Centre-South.

A different picture emerges from Figure 3b on the 5th percentile of the debt-asset distribution, with wider differences at the beginning of the period and convergence to about 10% by the end of the decade. Remarkably, firms in the Centre had a much lower level of debt at about 2% of the assets. Figure 3c on the 95% percentile is particularly striking. These are the most highly indebted firms, and potentially the most vulnerable to negative shocks. There is now a clear ranking among the three macro-areas of the country, with Southern firms exhibiting higher levels of debt uniformly over the sample period. All three areas show a decline after 2015, which accelerated sharply in 2019. This meant that their financial position was more solid when the pandemic crisis struck in 2020. There was indeed a steep increase in the debt ratios in 2020, but it was still lower than the peaks reached in 2015. The reduction in leverage prior to the COVID-19 crisis arguably lessened the impact of the disruption caused by the pandemic.

[Insert here Figures 3a, 3b and 3c]

Figures 4a-4c illustrate the evolution of the debt to asset ratios in five broad sectors: Agriculture, Forestry and Fishing, and Mining; Manufacturing; Construction; Wholesale and Retail Trade, and Repair of Motor Vehicles and Motorcycles; and Accommodation. From Figure 4a the sector that fared worst during the pandemic was Accommodation, with a sharp increase in the average debt-assets ratio in 2020 relative to 2019. This sector was also characterised by higher debt ratios over the whole sample period. Figure 4b confirms this increase even for the lowest 5% percentile, with the Construction sector also experiencing an increase albeit from a much lower base. Figure 4c on the 95% percentile again shows that Accommodation was the most exposed sector even before the pandemic, with systematically higher levels of debt relative to other sectors; it was also the sector that suffered the most during the COVID-19 crisis, with a steep increase in the ratio starting from an already high level.

[Insert here Figures 4a, 4b and 4c]

Figures 5a-5c distinguish firms according to the status during the pandemic of the sectors they belong to. In particular, we distinguish between sectors that remained active during the pandemic crisis, sectors that were suspended *ex lege* (*suspended sectors*), and industries that included some sub-sectors which were suspended and others which were not (*partially suspended sectors*). We divide the sectors according to the provisions of the *Decreto del Presidente del Consiglio dei Ministri* 10 April 2020 (Prime Minister's Decree): see Appendix A for details.

A remarkable aspect from Figure 5a is that the sectors which were forced to suspend their activity altogether already had the highest levels of the debt-to-assets ratios consistently through the sample period. Furthermore, they experienced the steepest increase in the average debt ratios in 2020 relative to the previous year. Figure 5c starkly illustrates that the most highly indebted among these firms had seen their leverage increase since 2010, and only in the past few years have they started to reduce their liabilities. Their debt ratios shot up again during the pandemic, much more steeply than for the firms operating in sectors that had remained at least partially active. The sectors which were forced to close were therefore the most vulnerable even prior to the COVID-19 crisis, and they suffered the most as a result of the pandemic. However, it seems that regardless of their status during the pandemic, most indebted firms were forced to accumulate more debt during the pandemic. Indeed, also those operating in active or partially suspended sectors increased their exposure with respect to 2019, even if this for these firms' debt is still lower in 2020 than in 2018. This pattern does not hold when considering less indebted firms (Figures 5a and 5b).

[Insert here Figures 5a, 5b and 5c]

Figures 6a-6c further break down firms both by geographical macro-area and by status. Figure 6a shows that there is a uniform ranking in debt ratios across the three macro-areas, with firms in suspended sectors exhibiting the highest ratios throughout the sample period followed by partially-suspended industries and finally by active industries. This ranking is inverted to some degree in the lowest 5% of the distribution of firms, with partially suspended sectors having a slightly higher debt ratios than the suspended firms. For the top 95% percentile, however, firms in the suspended sectors again have the highest debt ratios. In the South the levels of debt in 2010 were actually very similar across the three typologies of firms, with a gap opening up between the suspended and the two other sectors in the course of the decade. In the Centre suspended and partially-suspended sectors had the same initial levels of debt, with a discrepancy again opening up as the decade progressed. In the North a gap was already present in 2010, and became more marked as the sectors which were suspended during the pandemic experienced a severe deterioration in their debt ratios.

[Insert here Figures 6a, 6b and 6c]

4. Determinants of debt

In this section we explore the main determinants of leverage for Italian NFCs. Both theoretical and empirical literature on debt determinants is well-grounded and have identified a number of factors that influence capital structure decisions by firms.

First, a number of studies have highlighted the role of firm's size on leverage. Size is generally thought to be positively associated to leverage (Gonzalez and Gonzalez, 2012). Larger firms are more diversified and have a lower probability of being in financial distress. The lower expected bankruptcy costs enable them to take on more leverage (Ferri and Jones, 1979; Smith and Watts, 1992). However, bigger firms are also less affected by asymmetric information. Outside investors are able to access more information about bigger firms, hence the latter should find it easier to finance their activities via equity rather than debt. Moreover, bigger firms are typically denoted by greater cashflows from existing activities and this enables them to employ more internal resources (Rajan and Zingales, 1995). Ultimately, the impact of size on leverage might depend on country-specific institutional factors.

Second, more tangible-oriented firms are generally found to be more leveraged. They are likely to face lower costs of debt because of the availability of more collateralizable assets (Scott, 1977; Titman and Wessels, 1988; Harris and Raviv, 1991). Thus, we expect asset tangibility to have a positive impact on the debt-to-assets ratio.

Third, growth prospects and profitability matter too. Growth opportunities represent non-collateralizable assets, hence growing firms could find it more difficult to obtain credit because of the asset substitution effect (Bradley *et al.*, 1984; Titman and Wessels, 1988). On the other hand, according to the pecking order theory (Myers and Majluf, 1984) profitability is negatively related to leverage because firms prefer to rely first on internally generated funds for the financing of their investments. Firms resort to debt (and then equity) only when the former are not sufficient.

In general, all the factors recalled above influence capital structure decisions because they can be interpreted in terms of agency costs and other costs arising from asymmetric information.

Finally, depreciation should be negatively related to firm's indebtedness because it represents a non-debt tax shield. DeAngelo and Masulis (1980) show that tax deductions for depreciation substitute for the tax benefits associated with higher debt. Thus, firms with large non-debt tax shields should be less levered.

To explore the main determinants of firm's leverage, as a first step we rely on fixed effects OLS estimates that follow equation 1:

$$(Debt - to - Assets)_{it} = \alpha + \beta(FirmFeatures)_{it} + d_t + c_i + \varepsilon_{it} \quad (1)$$

All specifications also include year fixed effects (d_t) to account for temporal dynamics. Among $FirmFeatures$, as a proxy for size we alternatively use $Employment$, the number of firm's employees (in hundreds), and *Sales*, the amount of firm's sales (in ln). *Tangibility*, tangible over total assets, controls for firm's orientation towards tangible and collateralizable assets. *Ebitda*, EBITDA over total assets, controls for profitability while *ΔAssets* (annual percentage variation of total assets) and *ΔSales* (annual percentage variation of sales) account for growth prospects. Finally, depreciation scaled by total assets (*Depreciation*) serves as a proxy for non-debt tax shield. All variables, except from growth measures, enter our specifications lagged once to avoid simultaneity.

Table 1 reports our benchmark results. We first include only firm and year fixed effects (columns 1 to 4). Then, from column 5 to 8, we also saturate our regressions with province×year and sector×year fixed effects in order to control for idiosyncratic shocks hitting particular productive environments (at province or industry level) in specific years. Standard errors are robust to heteroskedasticity and are clustered at firm level from column 1 to 4, double clustered at firm and year level from column 5 to 8.

Surprisingly, both *Employment* and *Sales*, have a negative and significant coefficient. This stands in contrast to previous literature which suggests that bigger firms should be more levered because they find it easier to obtain loans, thanks to lower asymmetric information or because of their lower probability of financial distress. This result could be explained on the grounds that such firms are able to access equity markets, so that they might prefer to raise funds in the form of equity rather than debt. Rajan and Zingales (1995) find a similar negative relationship between size and leverage in Germany.

In line with our expectations, *Ebitda* as a measure of profitability has a negative impact on leverage. However, the coefficient is not significant at conventional values. The same is true for *Depreciation*. Also *Tangibility* has a counterintuitive impact on the debt-to-assets ratio. While a greater presence of collateralizable assets should incentivize firms to pile up more debt, its effect is negative and strongly significant. Finally, as expected *ΔAssets* and *ΔSales* show a negative and significant coefficient. First, growth prospects are not collateralizable so that growing firms have a higher agency cost of debt. Second, the variables might partially account for greater internal resources alongside with *Ebitda*.

[Insert here Table 1]

The surprising results in Table 1 might depend on two issues: i) the high heterogeneity affecting different geographical subsamples of firms as discussed in the previous sections, and ii) the OLS estimator that, by focusing only on the central tendency of the distribution does not allow for distinguishing the impact of explanatory variables for low- and highly-levered firms.

We account for the latter in the next section on quantile regressions. As for the former issue, we replicate our main specifications in subsamples of firms headquartered in the North, Centre and South, respectively. Results are reported in in Appendix B and do not prove useful in explaining ambiguous results.

Another result of notice from section 3 is that firms in sectors suspended (or partially suspended) *ex lege* during the pandemic already showed some signs of fragility before 2020. Firm fixed effects absorb sector dummies, hence we could not estimate the impact of belonging to a suspended sector on debt in previous estimates. To explore the issue, in Table 2 we replicate the estimation of equation 1 by resorting to random effects specifications. However, since the assumption of regressors uncorrelated with the firm-specific term is not realistic in our context, we also implement the *Correlated Random Effects Model* by Woolridge (2019). It applies a Mundlak-Chamberlain correction and allows unobserved heterogeneity to be correlated with observed covariates. In both cases, we are able to estimate the impact of two time invariant dummies, *Partially Suspended* and *Suspended.* The first takes value 1 if the firm operates in a sector that was partially suspended by the Prime Minister Decree of 10 April 2020, and 0 otherwise. The second takes value 1 if the firm operates in a sector that was fully suspended by the Prime Minister Decree of 10 April 2020, and 0 otherwise.

[Insert here Table 2]

Evidence from Table 2 is broadly in line with Table 1. However, *Ebitda* now becomes significant, pointing to the validity of the pecking-order theory in our sample. The same happens to *Depreciation*, contrary to the findings by DeAngelo and Masulis (1980). Importantly, Table 2 confirms the stylized facts discussed in section 3. Both the dummies *Partially Suspended Sectors* and *Suspended Sectors* are positive and significant. Moreover, the latter has a greater coefficient than the former. This suggests that, on average, firms operating in sectors that were fully suspended *ex lege* during the pandemic are the most levered during the period under scrutiny, followed by firms belonging to sectors that were partially suspended. Sectors that remained active during the pandemic were already those in which less fragile firms operate. In detail, belonging to a partially suspended sector brings about an increase of leverage amounting between 8 and 10% (20% one standard deviation of leverage), while operating in a fully suspended industry translates into a 11 to 13 % increase in the leverage ratio (26% one standard deviation).

5. Quantile regressions

The findings from the various OLS regressions of the previous section are somewhat mixed. One possible reason for these results is that we are trying to impose equality of coefficients across heterogeneous firms. In particular, highly indebted firms could exhibit a qualitative different behaviour from firms with lower levels of debt. In order to explore this possibility we estimate the model by using quantile regression methods (Koenker and Bassett, 1978).

This approach enables us to allow for different behavioural relationships over the distribution of firms by leverage (Fattouh, Harris and Scaramozzino, 2005, 2008).

We assume that the θ-th quantile of the conditional distribution of the dependent variable y_{it} is linear in the vector of regressors x_{it}. The quantile regression model of the debt-assets ratio can be formulated as:

$$Quant_{\theta}(y_{lt}|x_{it}) = \alpha_{\theta} + \beta'_{\theta}x_{it} + \gamma_t + \delta_i + u_{\theta it} \tag{2}$$

where $Quant_{\theta}(y_{lt}|x_{it})$ is the θ-th conditional quantile of y_{it}, α_{θ} and the vector β_{θ} are the parameters to be estimated, γ_t are time dummies, δ_i are time-invariant firm-idiosyncratic error components, and where the disturbances $u_{\theta it}$ are such that its conditional expectation over each quantile is zero:

$$Quant_{\theta}(y_{lt}|u_{\theta it}) = 0 \tag{3}$$

Similar to binary models, dealing with individual effects in a quantile regression setting is difficult because the estimators suffer from the incidental parameter problem. Literature on the matter is only recently growing and a number of panel conditional quantile regression estimators are now becoming available. They differ in the way the treat the individual-specific component, on the assumptions one should accept in order to obtain unbiased results, and in the computational power needed to provide estimates. For instance, the fixed effect estimator by Machado and Silva (2019) relies on the Method of Moments but is biased when *n/T* is large (greater than 10), an issue that affects our data. Since in our panel the number of firms (*n*) is more than 1.6 million and *T*= 11, other fixed effects alternatives are also not feasible (*e.g.* Galvao and Wang, 2015; Galvao and Kato, 2016; Powell, 2022). Moreover, the literature on the matter has not reached a consensus on which estimator performs best. After carefully considering all the alternatives, we decided to follow Wooldridge (2010) and estimated a Correlated Random Effects Conditional Quantile model. Similar to the traditional Correlated Random Effects model, the estimation consists in augmenting the specification by including the firm-specific means of the covariates in a pooled quantile regression. Moreover, as suggested by the author, apart from year dummies we also include a number of time-invariant firm characteristics (*i.e.* sector, province, listing status and joint-stock company dummy) in the specification. This procedure approximates the firm-specific effect and is the first-best given the nature of our dataset.

Table 3 presents the results. The coefficients in the table pertain to the 5th, 25th, 50th, 75th, and 95th quantiles of the distribution of the debt-assets ratio. It is immediately apparent that a number of coefficients display sign reversals over the distribution of leverage, thus revealing heterogeneity in the behaviour of firms. The coefficient on employment is positive up until the median, but then turns to negative for the top quantiles of the distribution. The size of the firm is therefore positively associated with leverage for low to medium levels of debt, but negatively associated with leverage for high debt levels. Hence, size decreases information asymmetries and enables firm to take on more debt. However, such effect is valid only until a certain threshold of indebtedness, after which the constraint derived from over indebtedness prevails on the reduction of information asymmetries. Another possible explanation is that bigger overindebted firms may find it easier to resort to equity rather than accumulate further debt, in line with the pecking order theory, or to undertake major structural changes (*e.g.* M&A, debt restructuring). Profits are negatively associated with debt, consistent with pecking-order theories of capital structure, for all quantiles except the very first one, for which however the coefficient is very small in absolute value.

[Insert here Table 3]

The share of tangible assets now attracts a positive coefficient as expected, with again the exception of the most highly indebted firms for which the coefficient turns negative. The same holds true for the growth prospects of the firm, proxied by the change in assets, which are positive over most of the distribution but become negative for the top two quantiles. Even if growth prospects are not collateralizable and hence are associated to higher agency cost of debt, financial intermediaries might find it profitable to finance lean growing firms. When firms start to accumulate too much debt, they find it difficult to obtain additional funds by levering on their growth prospects. The only puzzling result is depreciation, which has a positive and almost always significant coefficient. From capital structure theories we would have expected a negative coefficient, because depreciation provides a non-debt tax shield and should therefore act as a disincentive to take outside loans.

Being in a sector which was fully or partially suspended always has a positive and significant effect on debt-assets ratios. The coefficients on fully suspended sectors are also much larger in magnitude than the corresponding coefficients for partially suspended sectors, with the only exception of the bottom 5th quantile. Debt levels where therefore significantly higher for firms in these categories.

These findings show that standard theories of capital structure are able to account for the behaviour of firms with low- to medium-debt ratios in the sample[5]. In general, our results show that highly indebted firms exhibit a qualitatively different behaviour with respect to the rest of the sample. Size, the share of tangible assets, and the growth of assets tends to be negatively associated with the debt-to-assets ratio for higher levels of leverage. Smaller firms and those with a lower share of tangible assets and slower growth prospects are therefore potentially more exposed to explosive increases in the debt-to-assets ratios, and could find themselves even more vulnerable to conditions of financial distress. This is also the result of a financial environment that provides few alternatives to debt. If raising funds via equity is only feasible for big and tangible-oriented players that are characterised by lower agency costs, smaller firms are first obliged to collect debt and then, if the latter excessively piles up,

[5] All our main results are confirmed if the growth prospects of the firms are proxied by the change in sales rather than by the change in assets.

they are not able to switch to equity and find themselves in a sort of debt trap. Past contributions have already shown how the ability by firms to access alternatives to debt is important to recover from financial shocks (Leary, 2009; Kahle and Stulz, 2013), and how smaller firms are at a disadvantage in this context (Driver and Muñoz-Bugarin, 2019). Our evidence seems to confirm that larger firms can avoid additional piling up of debt when already finding themselves in a situation of high indebtedness.

6. Debt and firms' exit

What are the consequences of excessive indebtedness on firms' survival? Too high a level of leverage is traditionally considered as one of the most prominent signs of financial vulnerability and as a leading factor in pushing firms towards voluntary exit or bankruptcy (Verwijmeren and Derwall, 2010; Balcaen *et al.*, 2011; Balcaen *et al.*, 2012). In this section we provide some evidence on the role of the debt-to-assets ratio as a predictor of firm's exit. Results are reported in Table 4. From column 1 to 5 we rely on Probit estimates and we include stepwise year, sector, province (NUTS3) fixed effects and additional firm level controls that previous literature deemed relevant as determinants of firm closure. Since we cannot include firm fixed effects in Probit models because of the incidental parameter problem, in columns 6 and 7 we switch to linear probability models that also account for firm-specific effects.

Our results indicate that leverage is a strong predictor of firm exit in all the specifications. In particular, a one unit increase in the ratio translates into a 11% increase in the probability of firm closure (one standard deviation increase in debt translates into a 5.5% greater probability of exit).

[Insert here Table 4]

To provide a more accessible visualization of our findings, we plot predictive margins coming from the specifications of column 5 and 7 in Figure 7. The chart indicates the probability of firm exit for each level of the debt-to-assets ratio. The Probit estimate suggests a more gentle increase in the probability of firm exit for lower values of leverage. All firms ranging from the 5^{th} to the 95^{th} percentile show a probability of closure lower than 20%. However, moving from an average value of debt (0.7) to the 95^{th} percentile (around 1.2) raises the probability of exiting from around 5 to around 8%. Results from the linear probability model are sharper, however, as they also account for firm-specific fixed effects. They suggest a homogeneous increase of more than 11% in the probability of exit for each unit increase in the debt-to-assets ratio. Thus, for instance, a firm with an average value of leverage has a probability of exiting the market amounting to about 4.5%, while it increases to around 10% for firms in the 95^{th} percentile. Both models assign a probability of closure of about 65% for firms with a debt-to-assets ratio of 6, the maximum value in our sample, and point to the need to put under control the piling up of debt in order to limit mass defaults by domestic firms.

[Insert here Figure 7]

7. Conclusions

This paper has studied the evolution of debt of Italian firms from 2010 until 2020, focusing on the aftermath of the financial crisis and on the first year of the COVID-19 pandemic. It has uncovered significant differences in the responses of firms to the shocks which affected the economy. On average, debt to assets ratios were lower at the onset of the pandemic than before the financial crisis, which meant that firms were in a sounder financial condition. On the other hand, highly leveraged firms were over-represented among the sample of firms which were suspended *ex lege* during the pandemic. Furthermore, they were less able to rely on their growth prospects or on the presence of tangible assets to sustain their debt levels. They are therefore in a vulnerable position as Italy was emerging from the pandemic crisis, and could be negatively affected by the current negative developments to the domestic and global economies.

In general, our results show that firms in the right tail of the distribution of firms by debt exhibit a qualitatively different behaviour in their financing decisions with respect to the rest of the distribution, regardless of the status of their sectors during the lock-down of the economy. Hence, this paper remarks the importance of adopting a quantile approach when analyzing firm's capital structure.

We document that excessive indebtedness is a significant predictor of firms' closure. In the post-pandemic situation of increasing energy prices and changes in the monetary policy stance, firms must cope with their high level of existing debt. In this context, we find that particularly small and intangible-oriented firms may find themselves in a fragile position. This is not only the results of internal factors, but also depends on a financial environment, the Italian one, that provides little alternative to debt financing.

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Table 1. Determinants of leverage, OLS regressions. Dependent variable: Debt-to-assets ratio.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment (t-1)	-0.00319***		-0.00263***		-0.00317**		-0.00256**	
	(0.000838)		(0.000735)		(0.000998)		(0.000864)	
Ebitda (t-1)	-0.00659	-0.00636	-0.00638	-0.00601	-0.00570	-0.00549	-0.00551	-0.00517
	(0.00382)	(0.00367)	(0.00369)	(0.00345)	(0.00335)	(0.00320)	(0.00324)	(0.00301)
Tangibility (t-1)	-0.0583***	-0.0205***	-0.0305***	0.00675	-0.0555***	-0.0182**	-0.0273***	0.0103
	(0.00479)	(0.00548)	(0.00512)	(0.00601)	(0.00485)	(0.00548)	(0.00538)	(0.00572)
ΔAssets	-0.0442***	-0.0650***			-0.0414***	-0.0620***		
	(0.00312)	(0.00367)			(0.00135)	(0.00244)		
Depreciation (t-1)	0.00129	0.00136	0.00115	0.00114	0.00125	0.00131	0.00111	0.00110
	(0.000845)	(0.000855)	(0.000832)	(0.000825)	(0.000844)	(0.000854)	(0.000831)	(0.000824)
Sales (ln, t-1)		-0.0266***		-0.0346***		-0.0264***		-0.0346***
		(0.00143)		(0.00159)		(0.00164)		(0.00176)
ΔSales			-0.00465***	-0.0249***			-0.00393***	-0.0242***
			(0.000827)	(0.00141)			(0.000677)	(0.00143)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nuts3*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,937,848	6,083,210	5,936,927	6,082,724	5,262,616	5,389,763	5,261,734	5,389,308
R-squared	0.742	0.742	0.741	0.741	0.751	0.751	0.750	0.750

Estimation method: OLS. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level from column 1 to 4; double clustered at firm and year level from column 5 to 8) in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 2. Determinants of leverage, OLS regressions. Dependent variable: Debt-to-assets ratio. Correlated Random Effects and Random Effects models.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment (t-1)	-0.00310***	-0.00268***			-0.00250***	-0.00233***		
	(0.000753)	(0.000908)			(0.000636)	(0.000799)		
Ebitda (t-1)	-0.00694*	-0.00816*	-0.00671*	-0.00787*	-0.00671*	-0.00796*	-0.00633*	-0.00755*
	(0.00392)	(0.00433)	(0.00377)	(0.00416)	(0.00380)	(0.00423)	(0.00359)	(0.00400)
Tangibility (t-1)	-0.0620***	-0.105***	-0.0236***	-0.0603***	-0.0325***	-0.0798***	0.00504	-0.0365***
	(0.00422)	(0.00343)	(0.00417)	(0.00340)	(0.00418)	(0.00341)	(0.00416)	(0.00339)
ΔAssets	-0.0463***	-0.0491***	-0.0671***	-0.0691***				
	(0.000668)	(0.000642)	(0.000743)	(0.000695)				
Depreciation (t-1)	0.00145*	0.00137*	0.00150*	0.00141*	0.00130*	0.00123*	0.00128*	0.00120*
	(0.000772)	(0.000728)	(0.000775)	(0.000731)	(0.000761)	(0.000713)	(0.000752)	(0.000704)
Sales (ln, t-1)			-0.0266***	-0.0257***			-0.0348***	-0.0313***
			(0.000300)	(0.000254)			(0.000409)	(0.000316)
ΔSales					-0.00516***	-0.00615***	-0.0256***	-0.0244***
					(0.000170)	(0.000168)	(0.000310)	(0.000260)
Partially suspended sector	0.0795***	0.0768***	0.0955***	0.0967***	0.0804***	0.0768***	0.0964***	0.101***
	(0.00106)	(0.00106)	(0.00111)	(0.00108)	(0.00106)	(0.00107)	(0.00112)	(0.00110)
Suspended sector	0.122***	0.124***	0.112***	0.112***	0.125***	0.127***	0.115***	0.112***
	(0.00130)	(0.00128)	(0.00127)	(0.00127)	(0.00132)	(0.00128)	(0.00128)	(0.00128)
Method	CRE	RE	CRE	RE	CRE	RE	CRE	RE
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates mean	Yes	No	Yes	No	Yes	No	Yes	No
Observations	6,073,536	6,073,536	6,216,511	6,216,511	6,072,608	6,072,608	6,216,025	6,216,025
R-squared	0.02	0.0169	0.032	0.0288	0.0174	0.0126	0.0307	0.0254

Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level from column) in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 3. Determinants of leverage, Quantile regressions.

VARIABLES	(1) 5th	(2) 25th	(3) 50th	(4) 75th	(5) 95th
Employment (t-1)	0.00269	0.00217***	0.000321*	-0.000567***	-0.00167***
	(0.00576)	(0.000124)	(0.000169)	(0.000145)	(0.000461)
Ebitda (t-1)	0.000310***	-0.149***	-0.317***	-0.452***	-0.657***
	(5.06e-05)	(0.00965)	(0.0148)	(0.0288)	(0.0938)
Tangibility (t-1)	0.00869	0.0628***	0.0320***	-0.0104***	-0.146***
	(0.00530)	(0.00469)	(0.00340)	(0.00353)	(0.0144)
ΔAssets	0.0652***	0.0556***	0.0161***	-0.00332***	-0.0636***
	(0.000814)	(0.000857)	(0.000385)	(0.000292)	(0.00231)
Depreciation (t-1)	0.000175	0.00240**	0.000963***	0.00592	0.704***
	(0.000803)	(0.00118)	(8.26e-05)	(0.0161)	(0.0734)
Partially suspended sectors	0.0411***	0.0349***	0.0185***	0.00724***	0.0335***
	(0.00156)	(0.00198)	(0.00149)	(0.000941)	(0.00368)
Suspended sectors	0.0250***	0.0834***	0.0712***	0.0365***	0.0681***
	(0.00178)	(0.00222)	(0.00166)	(0.00117)	(0.00591)
Constant	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
NUTS3 FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Covariates mean	Yes	Yes	Yes	Yes	Yes
Additional dummies	Yes	Yes	Yes	Yes	Yes
Observations	5,394,920	5,394,920	5,394,920	5,394,920	5,394,920

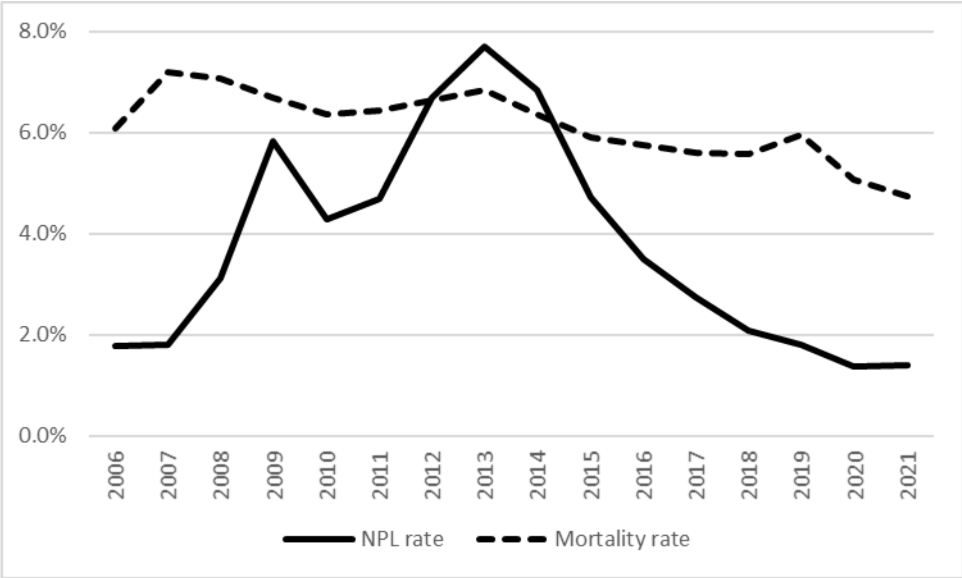
Estimation method: Correlated Random Effects Conditional Quantile regression. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level) in parentheses. Additional dummies: Listed firm, Joint stock firm. *** p<0.01, ** p<0.05, * p<0.10

Table 4. Impact of Debt-to-Assets ratio on the probability of firm exit.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES							
Debt-to-Assets (t-1)	0.299***	0.306***	0.305***	0.305***	0.420***	0.0970***	0.114***
	(0.00122)	(0.00124)	(0.00124)	(0.00125)	(0.00260)	(0.000543)	(0.000938)
Method	PROBIT	PROBIT	PROBIT	PROBIT	PROBIT	OLS	OLS
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	No	No
NUTS3 FE	No	No	No	Yes	Yes	No	No
Additional firm controls	No	No	No	No	Yes	No	Yes
Observations	7,827,382	7,827,382	7,827,382	7,695,474	4,627,116	7,827,382	4,702,351
R-squared	0.0179	0.0279	0.0329	0.039	0.1025	0.086	0.066

Dependent variable is a dummy that takes value 1 if the firm exits the market at time t, 0 otherwise. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level) in parentheses. Additional firm controls: Total assets (ln), working capital over total assets, short term debt over total debt, cash and other liquid assets over total assets, borrowing costs over sales, labour costs per capita. R-squared is the McFadden Pseudo R^2 from column 1 to 5, the overall R^2 in column 6 and 7. *** p<0.01, ** p<0.05, * p<0.10

Figure 1. Evolution of the non-performing loans rate (NFCs) and the mortality rate.



NOTES: The NPL rate is calculated only on NFCs. It comes from the Bank of Italy Statistical Database. The mortality rate is the ratio of de-registered to active firms. It comes from Movimprese by Infocamere.

Figure 2. Evolution of debt to assets ratio, 2010–2020.

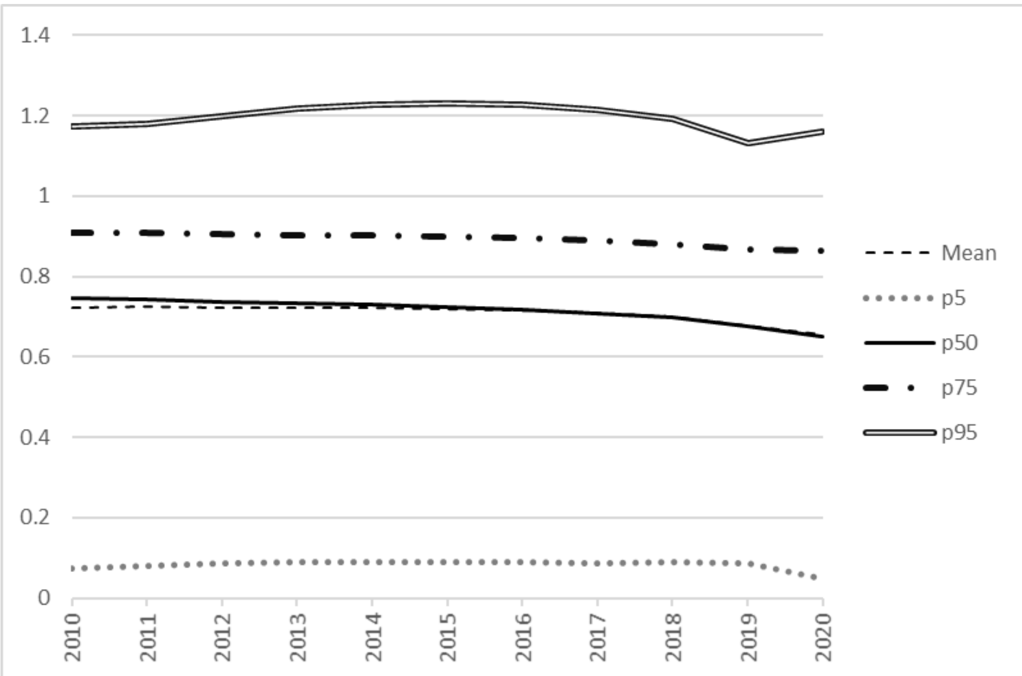


Figure 3a. Evolution of debt to assets ratio by macroarea, 2010–2020: mean ratio.

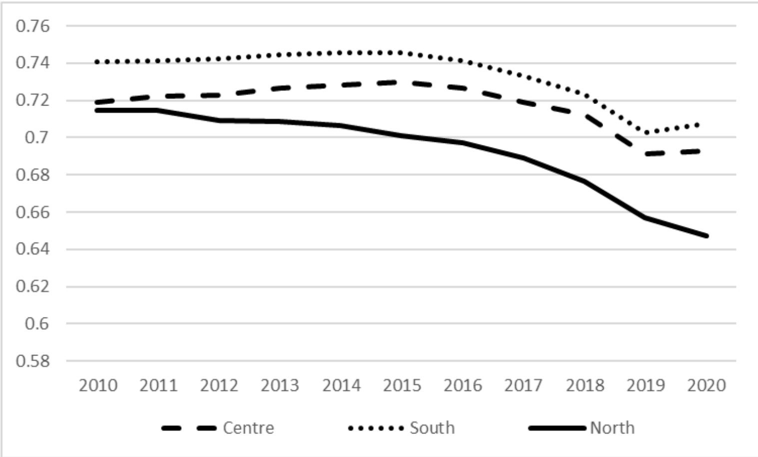


Figure 3b. Evolution of debt to assets ratio by macroarea, 2010–2020: P5.

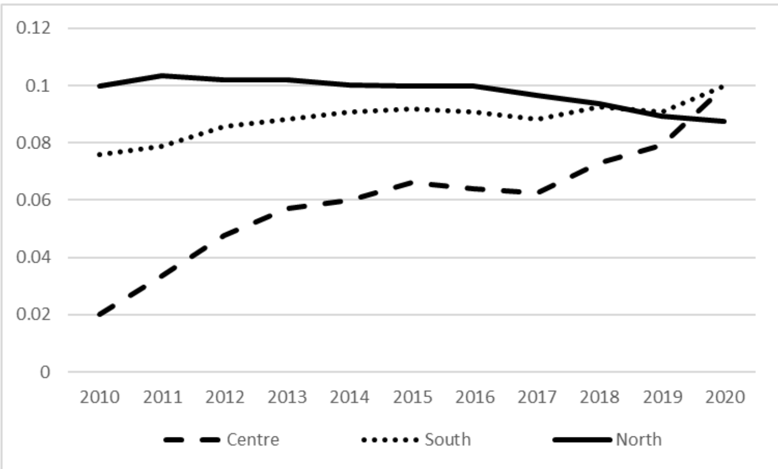


Figure 3c. Evolution of debt to assets ratio by macroarea, 2010–2020: P95.

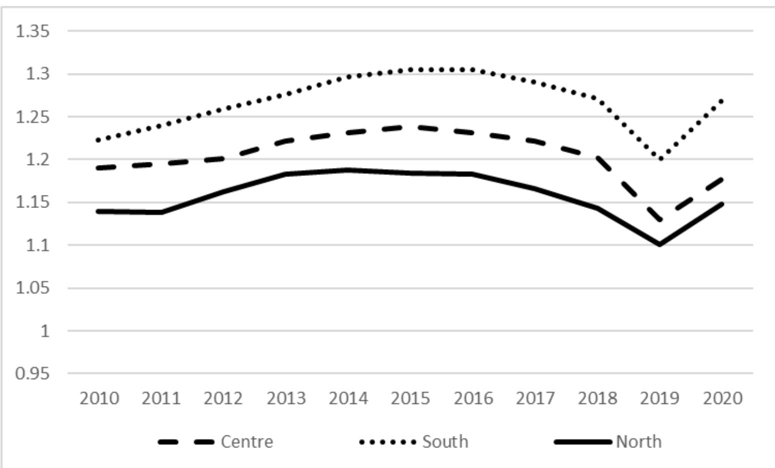


Figure 4a. Evolution of debt to assets ratio by sector, 2010–2020: mean ratio.

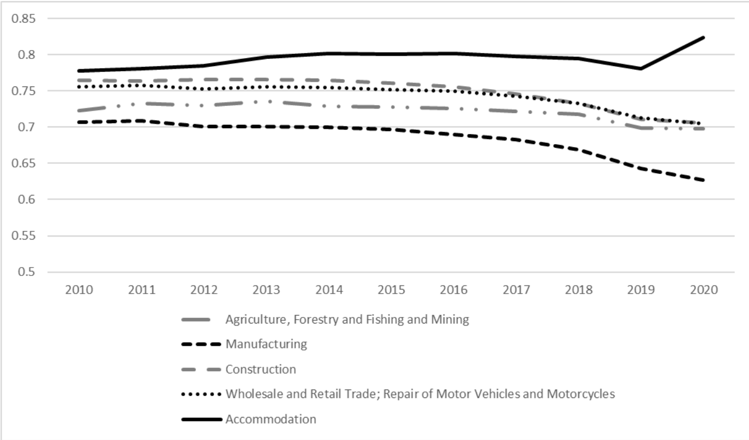


Figure 4b. Evolution of debt to assets ratio by sector, 2010–2020: P5.

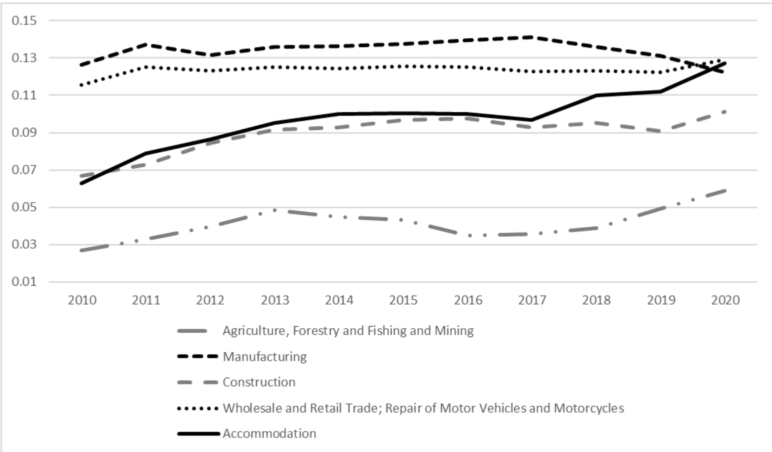


Figure 4c. Evolution of debt to assets ratio by sector, 2010–2020: P95.

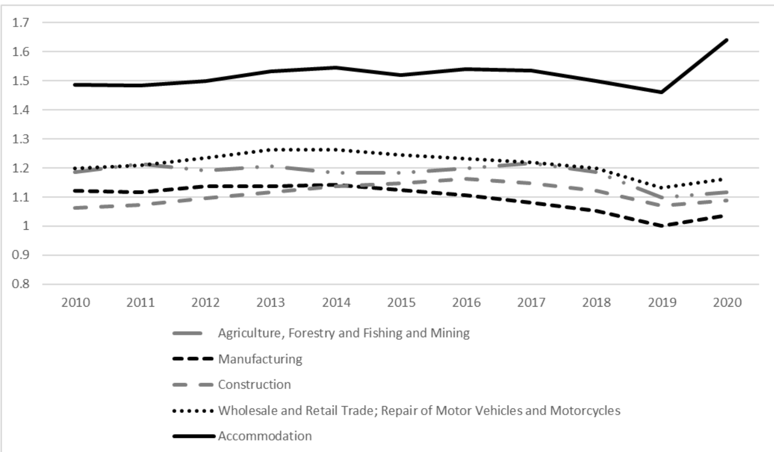


Figure 5a. Evolution of debt to assets ratio by status, 2010–2020: mean ratio.

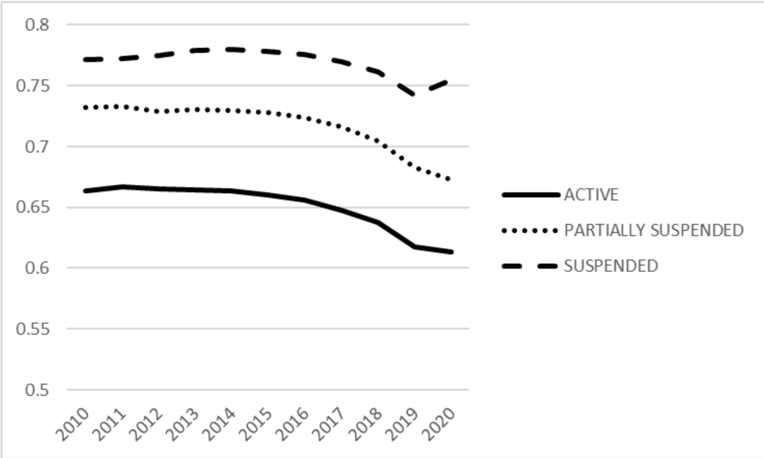


Figure 5b. Evolution of debt to assets ratio by status, 2010–2020: P5.

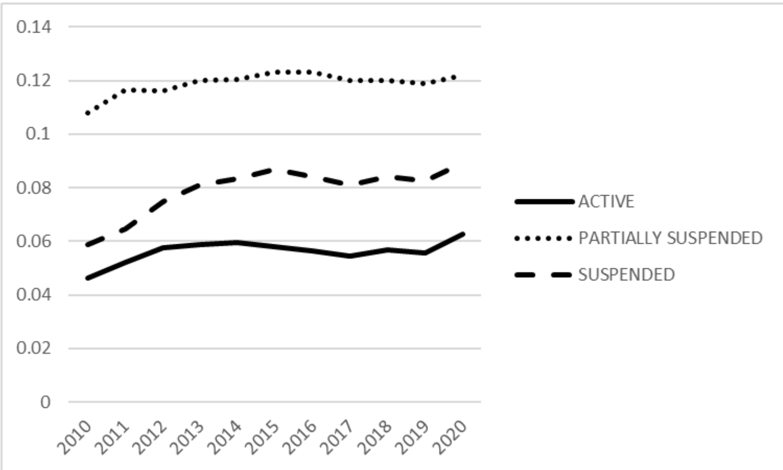


Figure 5c. Evolution of debt to assets ratio by status, 2010–2020: P95.

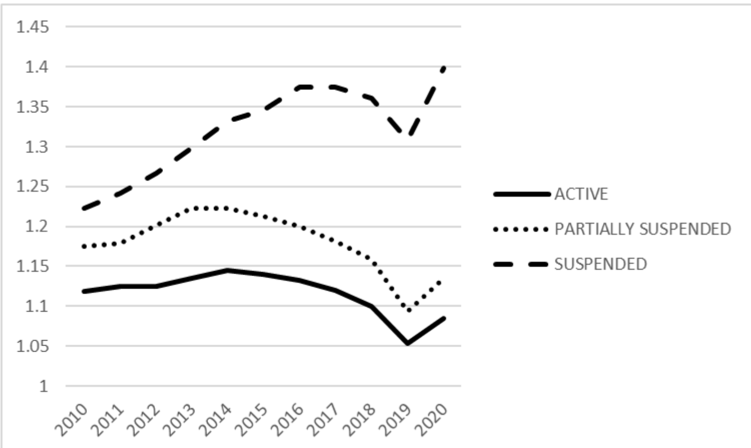


Figure 6a. Evolution of debt to assets ratio by status and macroarea, 2010–2020: mean ratio.

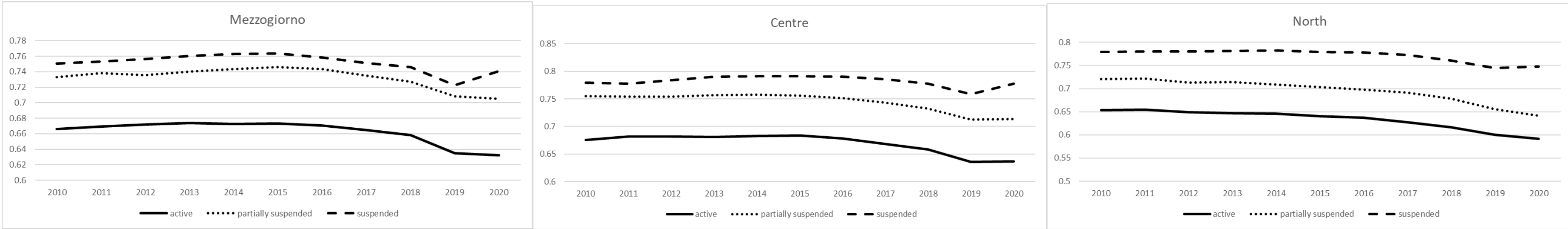


Figure 6b. Evolution of debt to assets ratio by status and macroarea, 2010–2020: P5.

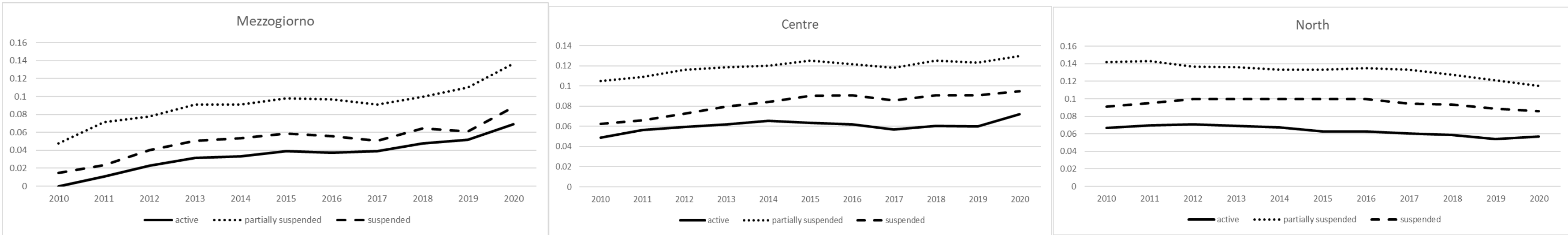


Figure 6c. Evolution of debt to assets ratio by status and macroarea, 2010–2020: P95.

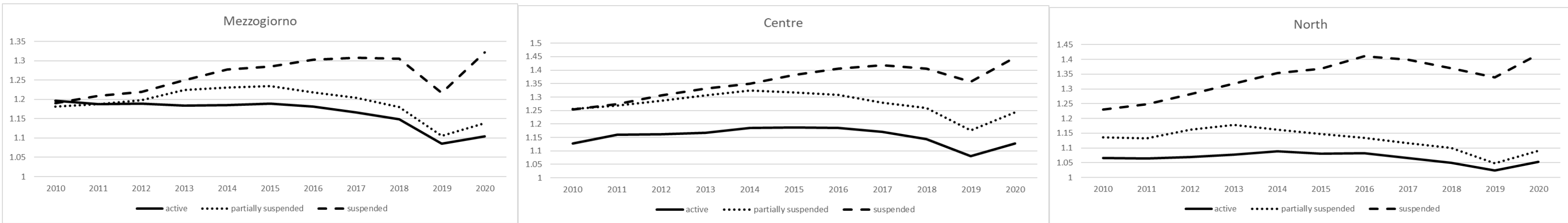
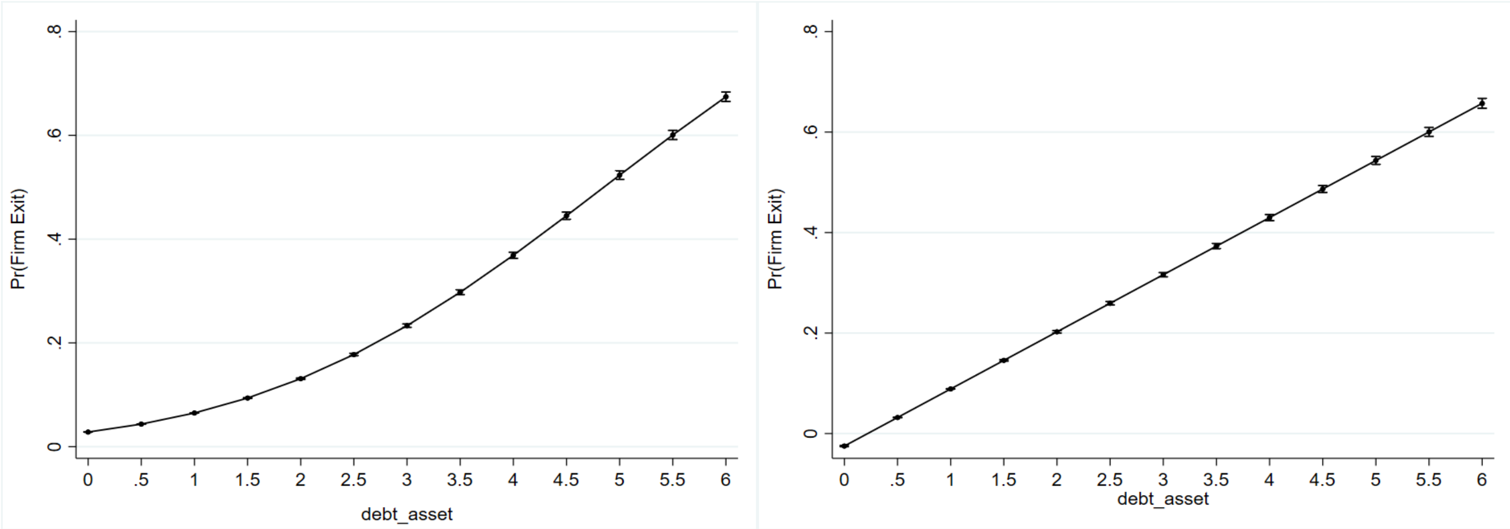


Figure 7. Impact of debt-to-assets ratio on the probability of firm exit. Predictive margins with 95% Confidence Intervals.

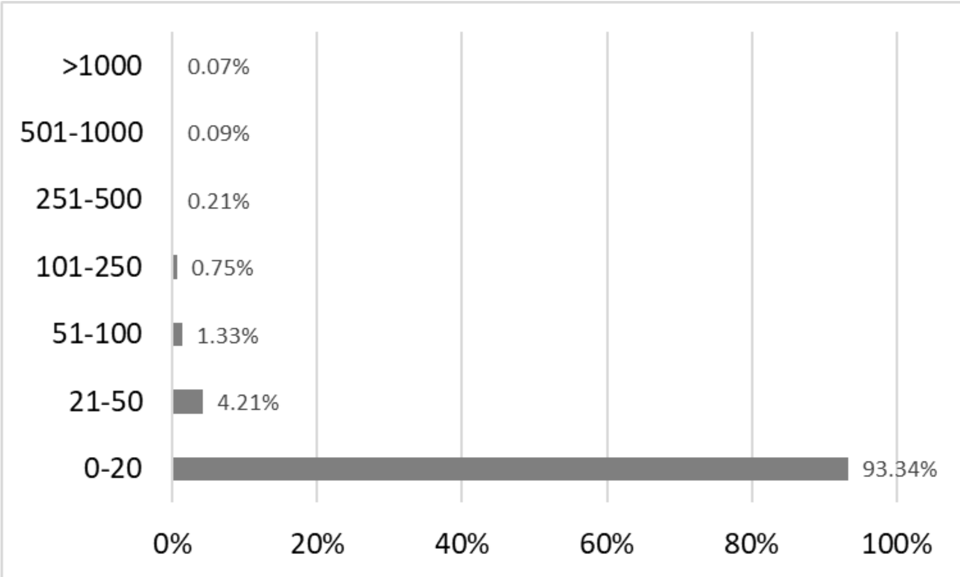


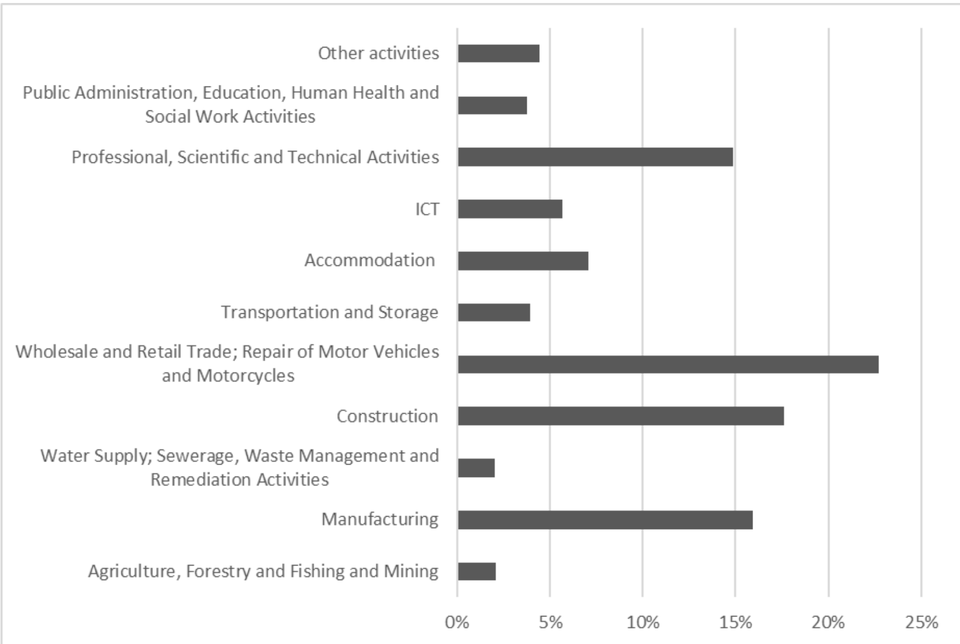
NOTES: The left-hand panel plots predictive margins calculated on the basis of the Probit specification of column 5 of Table 4. The right-hand panel plots predictive margins calculated on the basis of the OLS specification of column 7 of Table 4. Bars indicate 95 % confidence intervals.

Appendix A. Data description

We retrieve our data from two sources. Balance sheet data come from the Aida database by Bureau Van Dijk (Bureau Van Dijk, 2021). It provides information for the universe of Italian firms that are mandated by law to publish their accounting data. We retrieve data for firms that have published balance sheets at least once in the period between 2010 and 2020. Moreover, to avoid double counting, we consider consolidated balance sheets for firms that release both consolidated and individual accounting data. Overall, our initial dataset consists of 17,810,330 observations from 1,751,829 firms. Our main variable of interest, the debt to assets ratio, is available for 10,254,002 observations. In order to carry out our empirical analysis we further proceed with a number of cleaning procedures. First, we exclude from the dataset financial firms and those operating in related sectors (*i.e.* section K "Financial and Insurance activities" of the Nace rev.2 classification). Such firms follow specific financial strategies, whose study is beyond the scope of this paper. In this way we lose 2,235,840 observations. Second, to avoid the risk that our analysis be biased by extreme outliers which are probably due to misreporting, we exclude from our dataset firms that report a debt to assets ratio below the 1st percentile or above the 99th. The latter group mainly includes: i) firms that report a negative debt to assets ratio and ii) others that show a ratio in the order of tens of thousands. Overall, we drop about 90,000 observations following such step. Following the procedures above, we end up with an unbalanced sample of 15,484,827 observations, representing 1,649,731 firms. However, the debt to assets ratio is available for 8,704,693 observations from 1,617,940 firms. Attrition with other missing variables determines some limited drops in samples in our multivariate estimates. As Figure A.1 reports, small and micro enterprises (less than 50 employees) represent almost 98% of firms' observations in the dataset. The distribution of sectoral observations captures well the specialization of the Italian economy, after omitting financial firms.

Figure A. 1. Firms in the dataset by number of employees (top panel) and sectors (bottom panel).





Information on the status of the sectors (2-digits sectors, Nace rev. 2) during the pandemic come from INAIL (Istituto Nazionale per l'Assicurazione contro gli Infortuni sul Lavoro), the Italian public institute for workers protection (INAIL, 2020). The document divides the sectors (6-digits) in suspended *ex lege* and active, according to the provisions of the *Decreto Ministeriale* 25 March 2020 (Ministerial Decree by the Ministry of Economic Development) the *Decreto del Presidente del Consiglio dei Ministri* 10 April 2020 (Prime Minister's Decree). Hence, in our analysis we aggregate information at 2-digits level. In particular, we deem the 2-digit sector as fully active if all its subsectors (6-digits) were active according to the DPCM, fully suspended if all its subsectors (6-digits) were suspended from the DPCM, and partially suspended if within the 2-digit sector some subsectors were suspended and others were not. According to the DPCM, 41 sectors remained fully active, 18 were shut and 25 were partially shut.

In Table A1 we report the definitions of the variables used in the paper.

Table A 1 Variables' definitions.

Variable	Definition
Debt-to-Assets	Total debt divided by total assets
Employment	Number of employees divided by 100
Sales	ln(sales)
Ebitda	EBITDA divided by total assets
Tangibility	Tangible assets divided by total assets
ΔAssets	Difference between total assets (ln) at year t and total assets (ln) at year t-1
ΔSales	Difference between sales (ln) at year t and sales (ln) at year t-1
Depreciation	Depreciation divided by total assets

Appendix B. Determinants of debt in geographic sub-samples.

The ambiguous OLS results on the determinants of firms' debt reported in section 4 might arise because of firms' heterogeneity based on their geographic location. Italy is indeed characterized by high economic inequality among different areas of the country, with Mezzogiorno regions historically lagging behind Central and Northern ones in terms of economic development and performance. In our contexts, the same structural factors that determine such heterogeneity might also affect corporate finance decisions. To this aim, we replicate the specifications of Table 1 and investigate leverage's determinants in the three macro-areas (North, Centre and Mezzogiorno). Results are reported in Tables B.1, B.2 and B.3.

Findings for Northern firms are in line with those reported in Table 1. Size and tangibility are still negatively associated to leverage, while profitability and nondebt tax shield do not have a significant impact on debt. Estimates for firms from the Centre and the South provide a blurrier picture. First, while *Sales* still has a strongly negative influence on the debt-to-assets ratio, *Employment* loses significance in some specifications of both subsamples. In the Centre, the coefficient of *Tangibility* switches sign when included alongside with *Sales* and becomes positive and significant, as expected. Interestingly, our profitability proxy becomes significant in the Centre and, in line with our expectation, is negatively related to leverage. On the other hand, *Depreciation* turns significant in the South but, contrary to the literature predictions, its coefficient is positive. In general, even if the estimates in geographic subsamples remark the presence of a certain degree of heterogeneity in capital structure of Italian NFCs, results are difficult to interpret and they do not explain the counterintuitive results emerging from the overall sample.

Table B.1. Determinants of leverage, OLS regressions. Dependent variable: Debt-to-assets ratio. North subsample.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment (t-1)	-0.00389**		-0.00316**		-0.00366**		-0.00298*	
	(0.00148)		(0.00128)		(0.00152)		(0.00131)	
Ebitda (t-1)	-0.00343	-0.00328	-0.00333	-0.00310	-0.00287	-0.00274	-0.00278	-0.00258
	(0.00219)	(0.00208)	(0.00213)	(0.00196)	(0.00184)	(0.00174)	(0.00178)	(0.00163)
Tangibility (t-1)	-0.0616***	-0.0269***	-0.0330***	-0.00122	-0.0553***	-0.0217**	-0.0264**	0.00525
	(0.00786)	(0.00750)	(0.00849)	(0.00831)	(0.00757)	(0.00721)	(0.00831)	(0.00752)
ΔAssets	-0.0510***	-0.0720***			-0.0477***	-0.0686***		
	(0.00349)	(0.00398)			(0.00133)	(0.00253)		
Depreciation (t-1)	0.000907	0.000974	0.000749	0.000743	0.000837	0.000904	0.000686	0.000680
	(0.000553)	(0.000560)	(0.000548)	(0.000543)	(0.000537)	(0.000544)	(0.000535)	(0.000530)
Sales (ln, t-1)		-0.0304***		-0.0399***		-0.0301***		-0.0401***
		(0.00172)		(0.00185)		(0.00196)		(0.00199)
ΔSales			-0.00507***	-0.0277***			-0.00444***	-0.0272***
			(0.000819)	(0.00151)			(0.000739)	(0.00162)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nuts3*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	2,855,738	2,915,585	2,855,319	2,915,370	2,538,712	2,591,142	2,538,291	2,590,925
R-squared	0.746	0.748	0.745	0.747	0.757	0.758	0.756	0.758

Estimation method: OLS. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level from column 1 to 4; double clustered at firm and year level from column 5 to 8) in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table B.2. Determinants of leverage, OLS regressions. Dependent variable: Debt-to-assets ratio. Centre subsample.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment (t-1)	-0.00260		-0.00200		-0.00304*		-0.00237*	
	(0.00140)		(0.00114)		(0.00147)		(0.00118)	
Ebitda (t-1)	-0.0326***	-0.0319***	-0.0313***	-0.0298***	-0.0295***	-0.0287***	-0.0283***	-0.0268***
	(0.00896)	(0.00870)	(0.00861)	(0.00818)	(0.00819)	(0.00792)	(0.00788)	(0.00743)
Tangibility (t-1)	-0.0441***	-0.00728	-0.0167*	0.0182*	-0.0426***	-0.00568	-0.0146	0.0217**
	(0.00777)	(0.00877)	(0.00765)	(0.00853)	(0.00850)	(0.00955)	(0.00851)	(0.00898)
ΔAssets	-0.0503***	-0.0721***			-0.0472***	-0.0687***		
	(0.00363)	(0.00426)			(0.00231)	(0.00349)		
Depreciation (t-1)	0.00383	0.00401	0.00369	0.00375	0.00443	0.00461	0.00430	0.00438
	(0.00442)	(0.00435)	(0.00446)	(0.00438)	(0.00434)	(0.00427)	(0.00438)	(0.00429)
Sales (ln, t-1)		-0.0273***		-0.0356***		-0.0269***		-0.0355***
		(0.00165)		(0.00191)		(0.00189)		(0.00213)
ΔSales			-0.00614***	-0.0270***			-0.00528***	-0.0260***
			(0.000996)	(0.00174)			(0.000850)	(0.00178)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nuts3*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	1,427,339	1,471,818	1,427,127	1,471,705	1,285,453	1,325,519	1,285,243	1,325,408
R-squared	0.741	0.741	0.740	0.740	0.752	0.751	0.751	0.751

Estimation method: OLS. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level from column 1 to 4; double clustered at firm and year level from column 5 to 8) in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table B.3. Determinants of leverage, OLS regressions. Dependent variable: Debt-to-assets ratio. South subsample.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment (t-1)	-0.00244**		-0.00211**		-0.00216		-0.00167	
	(0.000771)		(0.000756)		(0.00146)		(0.00131)	
Ebitda (t-1)	-0.0386	-0.0370	-0.0374	-0.0353	-0.0349	-0.0335	-0.0339	-0.0321
	(0.0231)	(0.0221)	(0.0222)	(0.0210)	(0.0219)	(0.0212)	(0.0212)	(0.0201)
Tangibility (t-1)	-0.0569***	-0.0208**	-0.0314***	0.00670	-0.0568***	-0.0208*	-0.0304**	0.00770
	(0.00888)	(0.00889)	(0.00898)	(0.00893)	(0.00982)	(0.00984)	(0.00970)	(0.00968)
ΔAssets	-0.0322***	-0.0496***			-0.0305***	-0.0476***		
	(0.00264)	(0.00289)			(0.00159)	(0.00205)		
Depreciation (t-1)	0.0115***	0.0114***	0.0113***	0.0111***	0.0120***	0.0120***	0.0118***	0.0117***
	(0.000928)	(0.000848)	(0.000995)	(0.000988)	(0.00122)	(0.00121)	(0.00114)	(0.00119)
Sales (ln, t-1)		-0.0194***		-0.0242***		-0.0193***		-0.0242***
		(0.00141)		(0.00191)		(0.00152)		(0.00205)
ΔSales			-0.00320***	-0.0180***			-0.00251***	-0.0173***
			(0.000785)	(0.00141)			(0.000622)	(0.00143)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nuts3*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry*Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	1,589,488	1,628,295	1,589,238	1,628,168	1,438,451	1,473,102	1,438,200	1,472,975
R-squared	0.730	0.729	0.729	0.728	0.739	0.738	0.739	0.738

Estimation method: OLS. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. Robust standard errors (clustered at firm level from column 1 to 4; double clustered at firm and year level from column 5 to 8) in parentheses. *** p<0.01, ** p<0.05, * p<0.10