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Debt and financial fragility: Italian non-financial companies after the pandemic

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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. We use quantile regressions to assess the vulnerabilities of the most indebted firms. On average Italian non-financial companies (NFCs) reduced their indebtedness over the sample period, a trend which continued 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 for which the trend of declining indebtedness was reversed. Moreover, sectors that were suspended during the first lockdown already had the highest levels of the debt-to-assets ratios, and experienced the steepest increase in debt in 2020. Finally, our results show that highly indebted firms exhibit a qualitatively different behaviour compared to the rest of the sample. Excessive debt build-up severely increases the likelihood of non-financial companies exiting the market.

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; Hennessy, 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 (Jordà 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 outbreak 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 (Becker et al., 2020). 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 address the following key questions.

- First, did highly indebted firms exhibit a qualitatively different behaviour compared to less indebted firms?
- Second, what factors could explain this difference in behaviour?
- Finally, does excessive indebtedness constitute a significant predictor of firms' closure?

We analyse debt patterns of Italian firms from 2010 to 2020 by examining a detailed dataset on firms' balance sheets and using quantile

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The study was conducted while Beniamino Pisicoli was affiliated to the University of Rome Tor Vergata. Any views expressed are solely those of the author(s) and so cannot be taken to represent those of the Bank of England or to state Bank of England policy. This paper should therefore not be reported as representing the views of the Bank of England or members of the Monetary Policy Committee, Financial Policy Committee or Prudential Regulation Committee.

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regressions. Since we would miss relevant information by focusing only on the average firm, our approach consists in investigating several heterogeneities affecting the phenomenon under scrutiny and in order to assess the potential vulnerabilities of firms arising from the right tail of the debt-to-assets 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 a low base, would increase the cost of debt and put some pressure on the sustainability of debt especially for highly indebted 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 economic 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) experienced the steepest increase in the average debt ratios in 2020 relative to the previous year.

Our results also show different effects of the determinants of debt across the quantiles of the distribution. 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 providing few alternatives to debt. If raising funds via equity is only feasible for big and tangible-oriented players with lower agency costs, smaller firms are forced to resort to debt but then, if the latter excessively piles up, they become unable to switch to equity and find themselves in a sort of debt trap. This is in line with existing literature which shows 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). The detrimental effects of excessive leverage are also confirmed when estimating the impact of such variable on the probability of firms' survival. Many studies have shown that 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; Molina, 2005). In line with these studies, we find that excessive indebtedness is a significant predictor of firms' exit.

The rest of the article proceeds as follows. In section 2 we discuss the literature related to our study and introduce the institutional background of the Italian financial system. Section 3 describes our empirical setting and hypotheses. Section 4 provides some stylized facts on firms' indebtedness during the last decades, with particular attention to the first year of the pandemic, and investigates a number of heterogeneities characterizing the evolution of firms' debt over time. In section 5 we present our multivariate results on the determinants of leverage, from both OLS and quantile regressions, and on its impact on firms' survival. Section 6 concludes.

2. Related literature and institutional background

2.1. Literature Review

Our paper relates to different strands of literature. First, it enters the long-standing debate over the determinants of firms' debt choices. Both the theoretical and the empirical literature on debt determinants are well-grounded and have identified several 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 (González and González, 2012). Larger firms are more diversified and have a lower probability of being in financial distress. Their 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 can 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). The greater uncertainty associated with the pandemic might have exacerbated the asymmetric information between insiders and outside investors, potentially increasing the incentive for firms to use internal funds. 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. The pandemic is likely to have predominantly affected the valuation of intangible assets, thus increasing the possible importance of assets in securing debt.

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. The pandemic would have had a negative impact on profits, again increasing the pressure to take on external debt.

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 leveraged.

Our paper is also related to the empirical literature applying quantile regression methods (Koenker and Bassett, 1978) to explore different behavioural relationships over the distribution of firms by leverage. Indeed, most empirical studies employ traditional OLS regressions to analyse the determinants of firms' leverage. Some recent literature has however started to question such methodology, since it imposes equality of coefficients across heterogeneous firms. For instance, Fattouh et al. (2005) and Fattouh et al. (2008) show that highly indebted firms exhibit a different behaviour from firms with lower levels of debt. Implementing quantile regressions has become widespread in the literature (see for instance Oliveira et al., 2013; Sánchez-Vidal, 2014; Chay et al., 2015; Yıldırım and Çelik, 2021) as they provide more robust insights and in general prove superior to the traditional OLS.

Finally, our paper relates to the line of research studying the consequences of excessive indebtedness on firms' performance and survival. Many papers document the negative relationship between overleveraging and investment (see for instance Lang et al., 1996; Hennessy, 2004; Caldentey et al., 2019; Kalemli-Özcan, et al., 2022). Importantly, Molina (2005), Verwijmeren and Derwall (2010), Balcaen et al. (2011), and Balcaen et al. (2012) show that excessive debt accumulation can be seen as a prominent sign of financial vulnerability and as a leading factor in pushing firms towards voluntary exit or bankruptcy.

2.2. Institutional background

Our paper focuses on Italy, an advanced economy whose financial context is rather peculiar. Indeed, strategies in terms of capital structure by Italian non-financial companies (NFCs) are severely constrained by

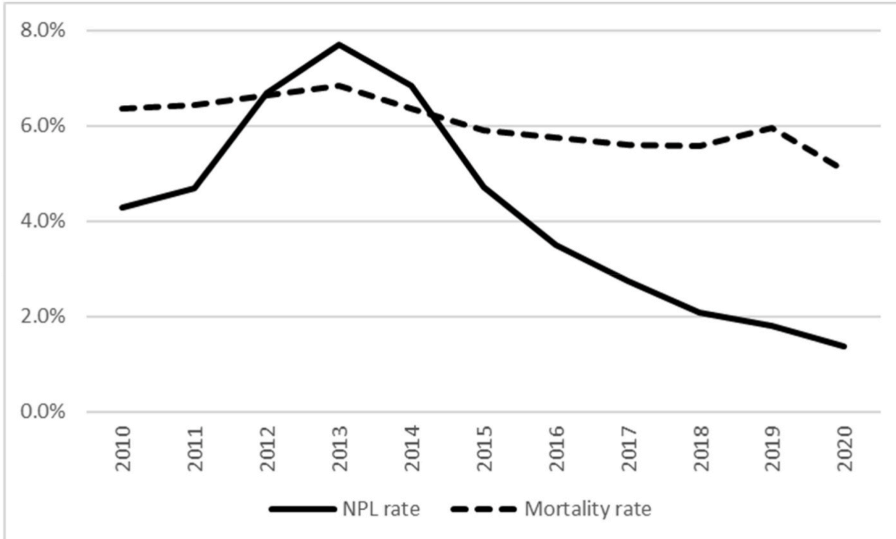


Fig. 1. Evolution of the non-performing loans (NPL) rate and the mortality rate of NFCs.
Notes: The NPL rate is calculated only on NFCs. It comes from the Bank of Italy Statistical Database. The mortality rate is the ratio of de-registered to active firms. It comes from Movimprese by Infocamere.

both external and internal factors. Firms find resorting to equity very costly because of the lack of institutional investors, of a high degree of risk aversion by households, and of government policies that have long incentivized households to invest in sovereign bonds instead of the equity market. 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 their 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]

The last few decades have proven 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 Fig. 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 first year of the pandemic, a pattern that has continued also in 2021 and 2022. 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 outbreak 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]

It should be pointed out, however, that the take up of these loans, even if government guaranteed, did affect the overall bankruptcy risk of the firms involved. Indeed, private creditors to a business in distress would have an incentive to push for bankruptcy of the firm rather than accept a restructuring of debt, in the knowledge that the government would intervene and meet the company's liabilities. Taking up the loans would therefore increase the firm's risk of default.

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

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

[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 causing 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.

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.

3. Empirical methodology and hypotheses

The aim of this paper is threefold. First, we are interested in documenting Italian firms' debt dynamics in the last decades, with particular focus on the first year of the Covid-19 pandemic. Second, we investigate leverage determinants of Italian firms with three questions in mind.

- Did highly indebted firms exhibit a qualitatively different behaviour compared to less indebted firms?
- What factors could explain this difference in behaviour?
- Did excessive indebtedness constitute a significant predictor of firms' closure?

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 order to provide a picture of the evolution of debt for Italian NFCs, we resort to a vast array of descriptive evidence. In particular, we disentangle leverage by year, macro-area and sector. Importantly, given that Italian NFCs are characterized by high heterogeneity, we would lose relevant information by focusing only on behaviour of the average firm. To capture different patterns affecting the rest of the distribution, we focus on different percentiles of the debt to assets ratio.

We then move to our multivariate analysis. To explore the main determinants of firm's leverage, as a first step we rely on fixed effects OLS estimates that follow equation (1):

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

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 Δ*Assets* (annual percentage variation of total assets) and Δ*Sales* (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. In order to estimate the coefficient of a number of time-invariant variables, we also implement the *Correlated Random Effects Model* by Wooldridge (2019). Moreover, we first estimate equation (1) in the full sample, then for robustness purposes: i) we replicate it in geographical sub-samples: ii) we control for potential endogeneity.

We run OLS regressions as a benchmark model to *indirectly* test the following hypothesis.

HYP1. Highly indebted firms exhibit a qualitatively different behaviour compared to less indebted firms.

As discussed in section 2, the theoretical corporate finance literature provides clear priors on the signs and statistical significance of the impact of such variables on leverage. If the included covariates show the expected signs, then highly indebted firms do not exhibit a different behaviour compared to less indebted firms, or, more likely, such differences are negligible. In this case, OLS is an adequate method to analyse firms' debt choices. On the contrary, if results from OLS estimates (even after controlling for geographical heterogeneity and endogeneity) are ambiguous, then we corroborate our **HYP1** and quantile regressions should be preferred.

As for the latter, 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:

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

where $Quant_\theta(y_{it}|x_{it})$ 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 the disturbances $u_{\theta it}$ are such that their conditional expectation over each quantile is zero:

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

Similarly to binary models, dealing with individual effects in a quantile regression setting is difficult because the estimators suffer from the incidental parameter problem. The literature on the matter is only recently developing and a number of panel conditional quantile regression estimators are now becoming available. They differ in the way they 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. Similarly 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.

The quantile setting *directly* tests the **HYP1**. If the impact of the regressors on debt-to-assets varies for firms in different percentiles of debt, then we document significant heterogeneity in firms' debt choices according to their level of debt. Moreover, different coefficients across quantiles also unveil what factors could explain this difference in behaviour.

Finally, we are interested in studying whether excessive indebtedness constitutes a significant predictor of firms' closure. To this aim we estimate the following equation:

$$(FirmExit)_{it}=\alpha+\beta(Debt-to-Assets)_{it-1}+\Upsilon(FirmFeatures)_{it}+d_t+c_i+\varepsilon_{it} \tag{4}$$

AIDA provides information on the year in which each firm has published its balance sheets. Since firms included in the database are mandated by law to publish their balance sheets, we interpret such data as the last year in which the firm operates, *i.e.* one year before its exit from the market. Hence, we create *FirmExit* as a dummy variable that takes value 1 if firm i exits the market at time t, 0 otherwise.[4] Firms may exit the market for various reasons. It may be a voluntary closure, they may go bankrupt, or they may be subject to a merger or to a takeover. We are not interested in the last case, since it does not necessarily

[4] We do not consider 2020 data in this exercise. Since 2020 is the last year available in our dataset, all firms active in 2020 report the same as the last one with an available balance sheet. Hence, we cannot distinguish between firms which will not operate in 2021 and those which will be active.

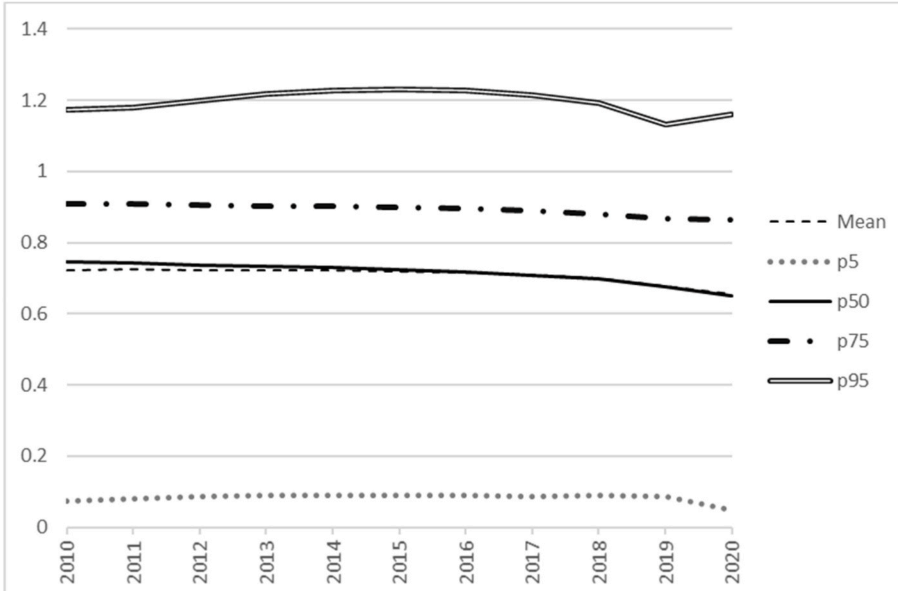


Fig. 2. Evolution of Debt-to-Assets in the period 2010–2020.

represent a negative scenario. Hence, we resort to Zephyr by Bureau Van Dijk (2023), a database listing all completed M&A operations since 1997. We retrieve all types of M&As (both foreign and domestic) occurred in Italy between 2010 and 2020 and combine such information with our data to refine our definition of market's exit. In particular, we drop from the dataset those observations regarding a firm that ceases its operations because it has been absorbed via a merger. We then estimate the impact of debt-to-assets on the probability of firm's exit, consisting only in closures or defaults.

Since *FirmExit* is a binary variable, we first estimate equation (4) via different *Probit* models. However, because of the incidental parameter problem, *Probit* models allow for the inclusion of year fixed effects (d_t) but not for firm fixed effects (c_i). Hence, we also consider linear probability models to control for firm-specific time-invariant issues. We test the following hypothesis, in line with the discussion in section 2:

HYP2. Debt is a significant predictor of firms' exit from the market and the higher the level of indebtedness the likelier is the exit.

We would corroborate **HYP2** if the coefficient associated to the debt-to-assets ratio is positive and significant and the relation between debt and the probability of firm exit is monotonic. To rule out that the relationship reverts after a certain threshold of debt, like in Ugur et al. (2022), we also augment equation (4) with the squared term of debt in a further test. Moreover, we distinguish between long- and short-term debt in order to detect potential heterogeneities according to debt maturity.

4. Descriptive analysis: evolution of debt

Our panel consists of 8,704,693 observations from 1,617,940 firms covering the period 2010–2020. Appendix A provides a more thorough description of the data. In the period under scrutiny, Italian firms report an average debt to assets ratio of 0.7, ranging from 0 to 6.

Given that firms are characterized by high heterogeneity, 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 Fig. 2 we plot the evolution of different percentiles of the debt to assets ratio over time, alongside the mean.

A number of points are worth noticing. First, in spite of the numerous financial shocks hitting the country in the last decades, debt to assets show, if anything, a 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 might come as a surprise, considering the rather cheap cost of credit in the Eurozone in the second part of the 2010s. It can however be explained by the need of banks to consolidate their balance sheets markedly affected by non-performing loans until 2015, and by 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 was suddenly stopped by the pandemic. Hence, the Covid-19 turmoil had its impact on the most highly indebted fragile firms.[5] Fig. 2 thus highlights the importance of closely investigating 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.

Indeed, the Italian economy has historically been characterised by marked income disparities between the North, the Centre, and the lagging southern regions of the country (the South, or *Mezzogiorno*: Boltho et al., 2018; Felice, 2019).[6] Fig. 3a shows the changes in the mean debt-assets ratio in the three macro-areas. In 2010 the average debt ratio was comparable across the three areas, with only a marginally 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 two

[5] Firms in the 95% percentile of the debt distribution exhibit a remarkable degree of persistence: estimation of a Markov transition matrix shows that the probability of remaining in this category in two consecutive years is 83.4%: the value of Shorrocks's (1978) overall measure of persistence $M^2 = 1 - \Pi\lambda_i$ is 0.926. For the two-year period 2019-20 (pre- and post-COVID), the probability of remaining in P95 is 87.4% and $M^2 = 0.927$.

[6] 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.

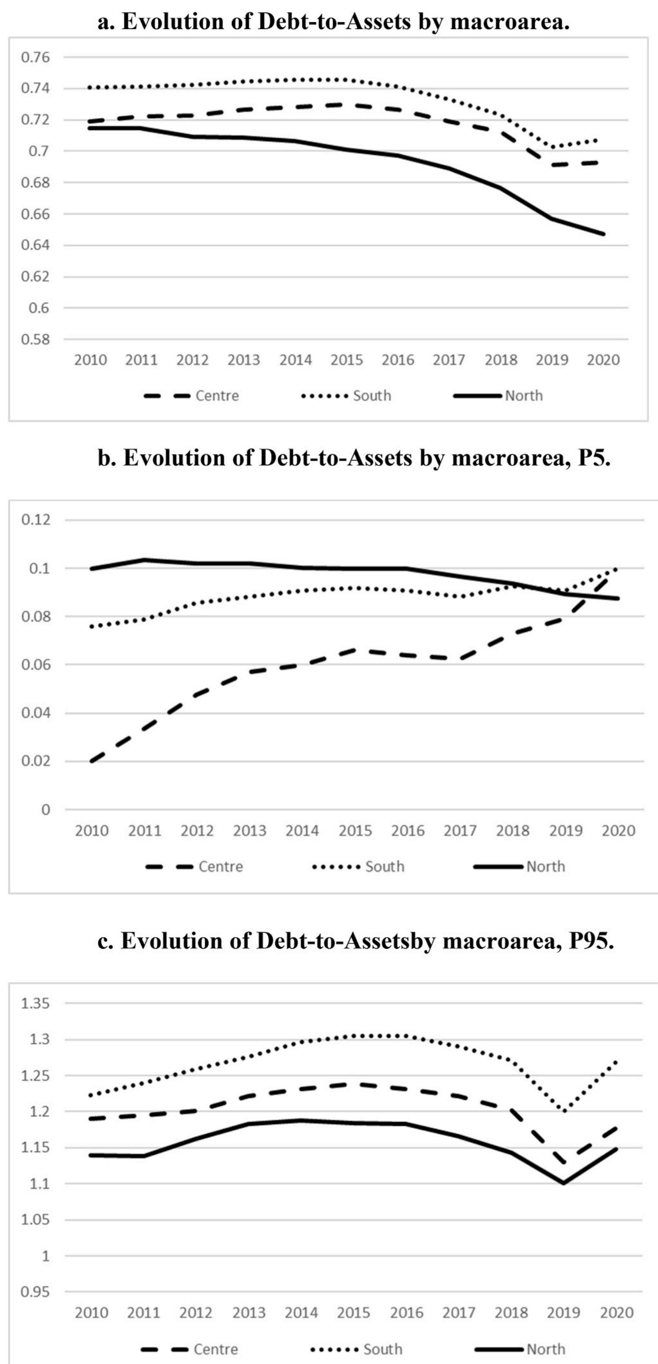


Fig. 3. a. Evolution of Debt-to-Assets by macroarea, mean. b. Evolution of Debt-to-Assets by macroarea, P5. c. Evolution of Debt-to-Assets by macroarea, P95.

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

A different picture emerges from Fig. 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. Fig. 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. Their financial position was thus 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.

Fig. 4a–c 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. Unsurprisingly, from Fig. 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 however also characterised by higher debt ratios over the whole sample period. Fig. 4b confirms this increase even for the lowest 5% percentile, with the Construction sector also experiencing an increase albeit from a much lower base. Fig. 4c on the 95% percentile confirms that Accommodation was the most exposed sector even before the pandemic, with systematically higher levels of debt; 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.

In Fig. 5a–c we distinguish firms according to the status of their sector during the pandemic. 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* April 10, 2020 (Prime Minister's Decree): see Appendix A for details.

A remarkable aspect from Fig. 5a is that those sectors which were forced to suspend their activity altogether already had the highest levels of the debt-to-assets ratios consistently throughout the whole sample period. Furthermore, they experienced the steepest increase in the average debt ratios in 2020 relative to the previous year. Fig. 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 had 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. Regardless of their status during the pandemic, most indebted firms were however forced to accumulate more debt during the pandemic. Indeed, also those firms operating in active or partially suspended sectors increased their exposure with respect to 2019, even if their debt was still lower in 2020 than in 2018. This pattern does not hold when considering less indebted firms (Fig. 5a and b).

Fig. 6a–c further break down firms both by geographical macro-area and by status. Fig. 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 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 during the course of the decade. In the Centre suspended and partially-suspended sectors had the same initial levels of debt, with a discrepancy 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.

The descriptive analysis in this section unveils several interesting patterns. In particular, it suggests that heterogeneity, at different sectoral and geographical levels, has a role in explaining the evolution of

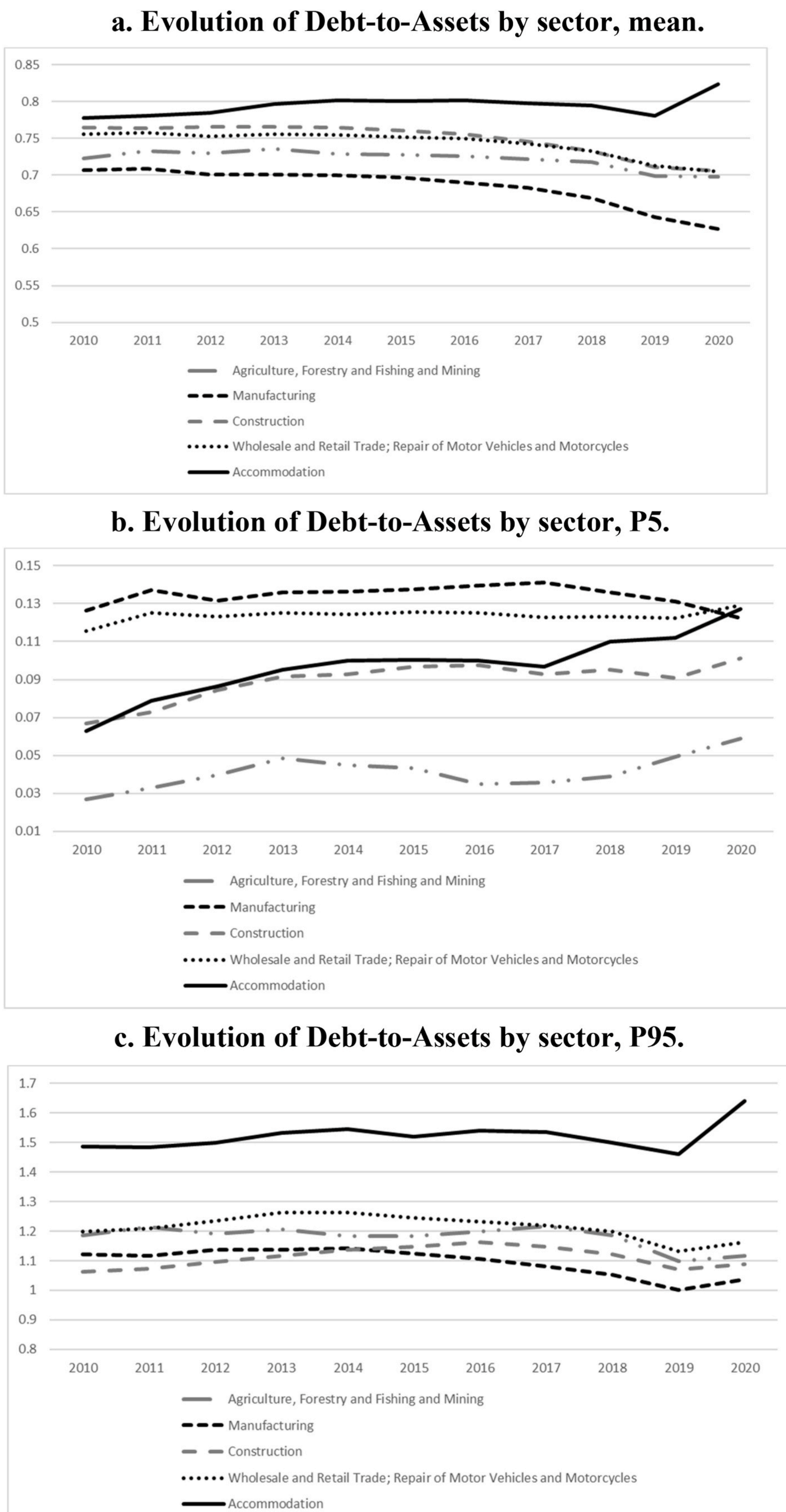


Fig. 4. a. Evolution of Debt-to-Assets by sector, mean.: b. Evolution of Debt-to-Assets by sector, P5, c. Evolution of Debt-to-Assets by sector, P95.

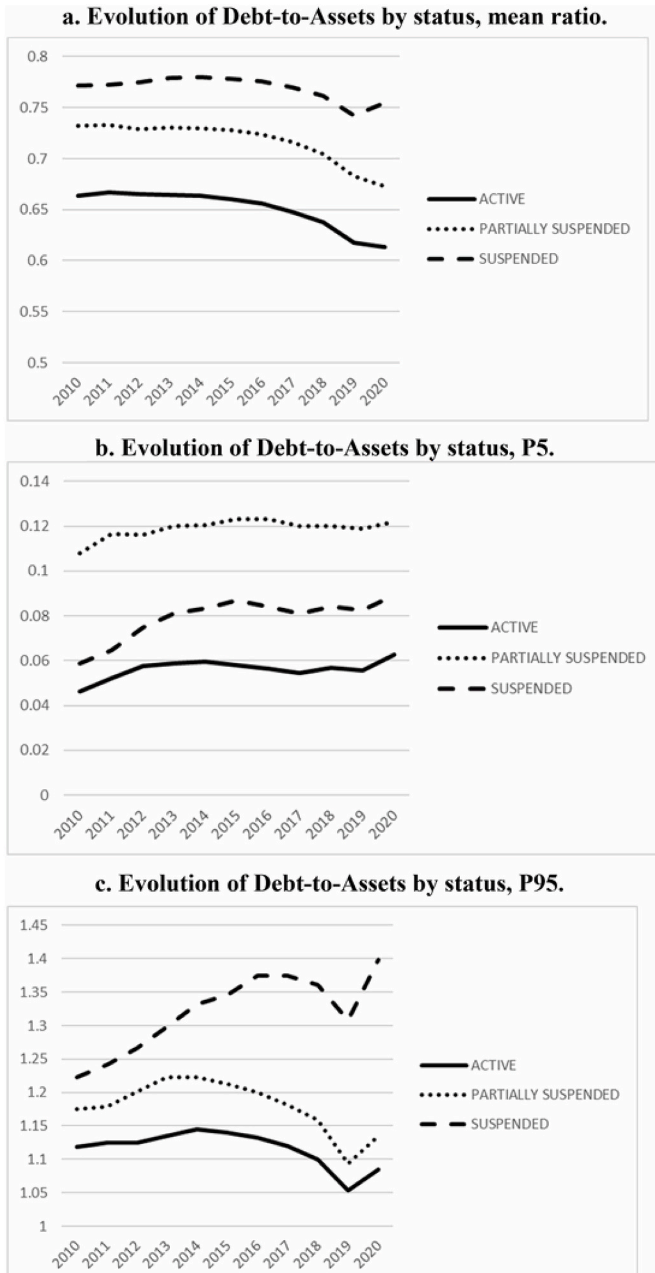


Fig. 5. a. Evolution of Debt-to-Assets by status, mean ratio, b. Evolution of Debt-to-Assets by status, P5, c. Evolution of Debt-to-Assets by status, P95.

debt of Italian firms in the last decades. To directly test this conjecture and to investigate whether it influences debt choices by NFCs, in the next section we move to a multivariate setting.

5. Multivariate analysis and main results

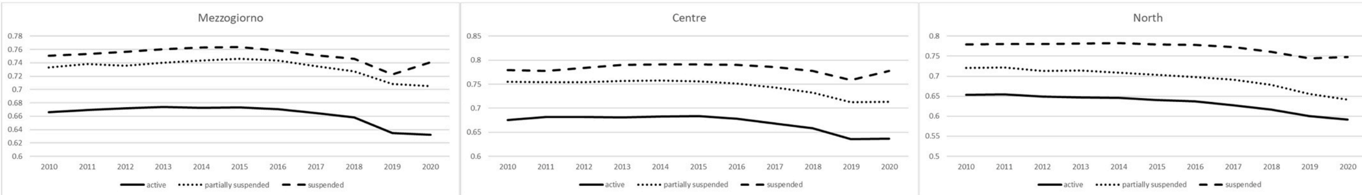
5.1. Determinants of debt: OLS and quantile regressions

We move to study the determinants of debt for Italian firms. Our first step is to estimate equation (1) via traditional OLS regressions and *indirectly* test **HYP1**. Indeed, we are interested in understanding whether OLS models provide results in line with the theoretical corporate finance literature. In this case, likely debt choices by firms in different debt percentiles are rather homogeneous and differences in behaviour non-existent or negligible. On the other hand, in case of ambiguous results, heterogeneities may be at work.

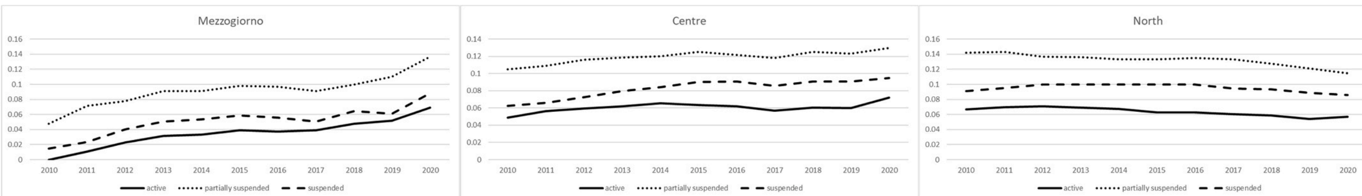
Table 1 reports our benchmark results. We first include only firm and year fixed effects (columns 1 to 4). Then, from column 5 to 8, we also saturate our regressions with province × year and sector × year fixed effects in order to control for idiosyncratic shocks hitting particular productive environments (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. However, their impact shows a high heterogeneity in terms of economic significance. While a one standard deviation increase in *Employment* leads to a marginal reduction in Debt-to-Assets (about 1% of one standard deviation), the impact of a standard deviation increase in *Sales* is much more meaningful (about 16% of a standard deviation). In any case, this stands in contrast to existing literature which suggests that bigger firms should be more levered because they find it easier to

a. Evolution of Debt-to-Assets by status and macroarea, mean.



b. Evolution of *Debt-to-Assets* by status and macroarea, P5.



c. Evolution of Debt-to-Assets by status and macroarea, P95.

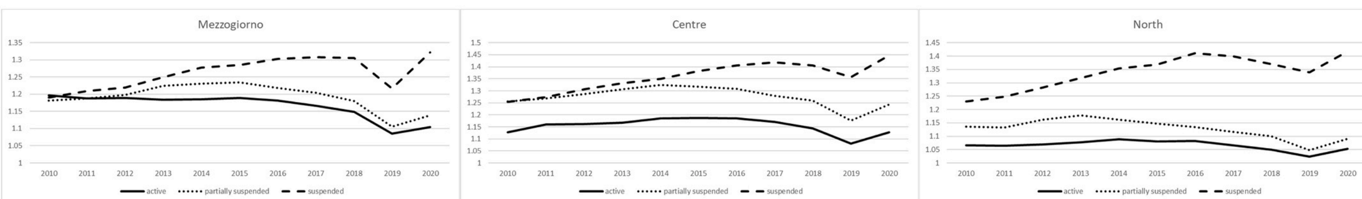


Fig. 6. a. Evolution of Debt-to-Assets by status and macroarea, mean, b. Evolution of Debt-to-Assets by status and macroarea, P5, c. Evolution of Debt-to-Assets by status and macroarea, P95. Solid black line active sectors, Dotted black line partially suspended sectors, Dashed black line suspended sectors.

Table 1
Determinants of leverage, OLS.

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. **Employment** is the number of employees divided by 100, **Sales** is defined as the natural log of sales, **Ebitda** is EBITDA divided by total assets, **Tangibility** is calculated as tangible assets divided by total assets, **ΔAssets** is the difference between total assets (ln) at year t and total assets (ln) at year t-1, **ΔSales** is the difference between sales (ln) at year t and sales (ln) at year t-1, **Depreciation** is calculated as depreciation divided by total assets. 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.

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 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*. *Tangibility* has a counterintuitive impact on the debt-to-assets ratio, even if its impact is not very significant from an economic perspective (one standard deviation increase translates into a reduction in Debt-to-Assets of about 1%

Table 2
Determinants of leverage, 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. **Estimation method: RE** stands for random effects, **CRE** stands for Correlated Random Effects à la Wooldridge (2019). **Employment** is the number of employees divided by 100, **Sales** is defined as the natural log of sales, **Ebitda** is EBITDA divided by total assets, **Tangibility** is calculated as tangible assets divided by total assets, **ΔAssets** is the difference between total assets (ln) at year t and total assets (ln) at year t-1, **ΔSales** is the difference between sales (ln) at year t and sales (ln) at year t-1, **Depreciation** is calculated as depreciation divided by total assets, **Partially suspended sector** is a dummy that takes value 1 if firm i belongs to a sector that was partially suspended during the pandemic, by the DPCM April 10, 2020, 0 otherwise, **Suspended sector** is a dummy that takes value 1 if firm i belongs to a sector that was partially suspended during the pandemic, by the DPCM April 10, 2020, 0 otherwise See Appendix A. for further details. Robust standard errors (clustered at firm level) in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

of its standard deviation). 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. In particular, a one standard deviation increase in *ΔAssets* leads to a reduction of between 4 and 7 % of a standard deviation in Debt-to-Assets, while a one standard deviation increase in *ΔSales* leads to a reduction of between 1 and 6% of a standard deviation in Debt-to-Assets. First, growth prospects are not

Table 3
Determinants of leverage, Quantile regressions.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	5th	25th	50th	75th	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. **Employment** is the number of employees divided by 100, **Sales** is defined as the natural log of sales, **Ebitda** is EBITDA divided by total assets, **Tangibility** is calculated as tangible assets divided by total assets, **ΔAssets** is the difference between total assets (ln) at year t and total assets (ln) at year t-1, **ΔSales** is the difference between sales (ln) at year t and sales (ln) at year t-1, **Depreciation** is calculated as depreciation divided by total assets, **Partially suspended sector** is a dummy that takes value 1 if firm i belongs to a sector that was partially suspended during the pandemic, by the DPCM April 10, 2020, 0 otherwise, **Suspended sector** is a dummy that takes value 1 if firm i belongs to a sector that was partially suspended during the pandemic, by the DPCM April 10, 2020, 0 otherwise See Appendix A. for further details. 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.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Debt-to-Assets (t-1)	0.299***	0.307***	0.305***	0.305***	0.420***	0.097***	0.110***
	(0.001)	(0.001)	(0.00124)	(0.001)	(0.003)	(0.0005)	(0.001)
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	7,827,182	7,827,182	7,827,182	7,695,279	4,626,952	7,827,182	4,702,182
R-squared	0.02	0.03	0.033	0.040	0.103	0.086	0.067

Dependent variable: **Firm Exit,** a dummy variable that takes value 1 if firm i exits the market at time t, 0 otherwise.Mergers are excluded from the dataset to avoid bias in the computation of the dummy. 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.

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*.[7]

The surprising results in Table 1 might depend on three issues: i) the high heterogeneity affecting different geographical subsamples of firms as discussed in the previous sections, ii) potential endogeneity affecting our estimates, and iii) 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 ii) later in this section. As for the former issues, we first replicate our main specifications in subsamples of firms headquartered in the North, Centre and South, respectively; then we consider an estimator that properly addresses endogeneity. Results are reported in in Appendixes B and C and do not prove useful in explaining ambiguous results.

Another result of notice from section 4 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 in previous estimates we could not assess the impact on debt of being in a suspended sector on debt. 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 Wooldridge (2019). This 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 April 10, 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 April 10, 2020, and 0 otherwise.

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 4. 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 already had the least less fragile firms. In detail, belonging to a partially suspended sector brings about an increase of Debt-to-Assets amounting to between 8 and 10 pp (about 20% of one standard deviation of leverage), while operating in a fully suspended industry translates into a 11 to 13 pp increase in the leverage ratio (about 26% of one standard deviation).

The findings from the various OLS regressions are somewhat mixed. One possible reason for these results is that we are imposing 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 re-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 et al., 2005,2008).

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 firms to take on more debt. However, such effect is valid only until a critical indebtedness threshold, after which the over-indebtedness constraint prevails on the reduction of information asymmetries. Another possible explanation is that bigger over-indebted 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). Smaller firms which already had high levels of debt may therefore have been particularly penalised by the pandemic because of their difficulties in taking on more debt.

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. Lower profits experienced during the pandemic could have led some firms to increase their indebtedness, especially in the presence of an elevated initial debt ratio.

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. A one standard deviation increase in *Tangibility* leads to an increase in Debt-to-Assets consisting in about 1% of its standard deviation in the left tail of the distribution, while its impact reverses to a reduction of about 3% of one standard deviation of

[7] The number of observations in Table 1 is not the same across the columns because of missing values among the control variables and different fixed effects. We re-estimated the table using the same set of observations for all the specifications and all our results are confirmed both in significance and magnitude.

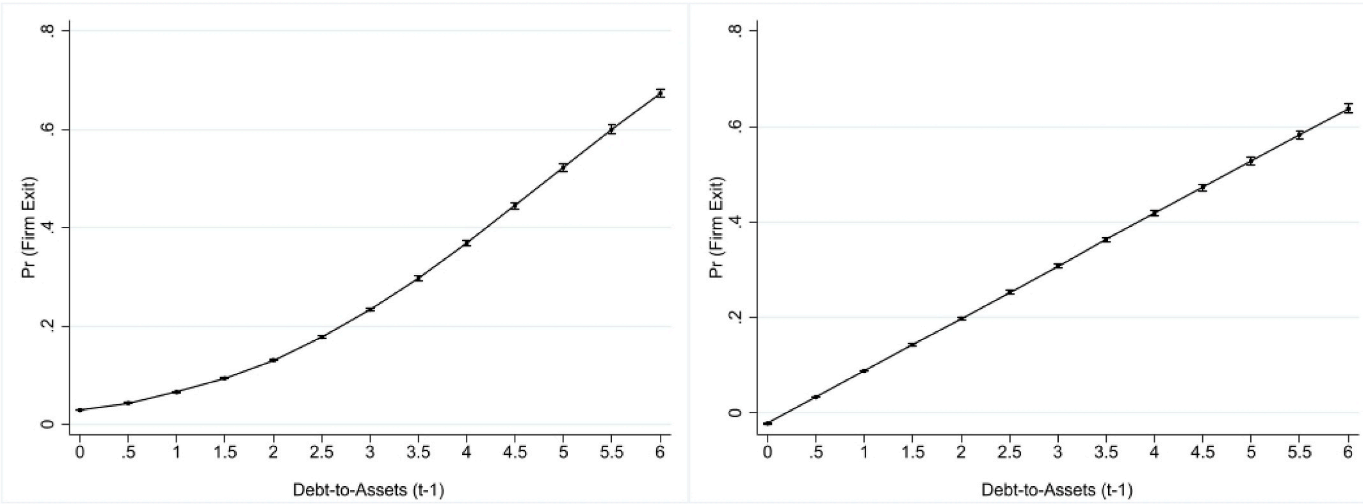


Fig. 7. Impact of Debt-to-Assets on the probability of firm exit, predictive margins with 95% Confidence Intervals.
NOTES: The left-hand panel plots predictive margins calculated on the basis of the Probit specification of column 5 of Table 4. The right-hand panel plots predictive margins calculated on the basis of the OLS specification of column 7 of Table 4. Bars indicate 95 % Confidence Intervals. Debt-to-Assets (t-1) on the x-axis, probability of firm exit on the y-axis.

Table 5
Impact of leverage on the probability of firm exit. Non-monotonicity and different maturities of debt.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Debt-to-Assets $_{(t-1)}$	0.083***	0.111***						
	(0.001)	(0.002)						
Debt-to-Assets ^{2} $_{(t-1)}$	0.003***	−0.0003						
	(0.000)	(0.000)						
ST Debt-to-Assets $_{(t-1)}$			0.092***	0.062***			0.108***	0.103***
			(0.001)	(0.001)			(0.001)	(0.002)
ST Debt-to-Assets ^{2} $_{(t-1)}$				0.010***				0.001***
				(0.000)				(0.000)
LT Debt-to-Assets $_{(t-1)}$					0.051***	0.029***	0.103***	0.102***
					(0.001)	(0.002)	(0.001)	(0.002)
LT Debt-to-Assets ^{2} $_{(t-1)}$						0.017***		−0.0005
						(0.001)		(0.001)
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
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
Additional firm controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,827,182	4,702,182	4,632,885	4,632,885	4,633,068	4,633,068	4,632,877	4,632,877
R-squared	0.086	0.067	0.061	0.062	0.052	0.052	0.065	0.065

Dependent variable: **Firm Exit,** a dummy variable that takes value 1 if firm i exits the market at time t, 0 otherwise. Mergers are excluded from the dataset to avoid bias in the computation of the dummy. **ST Debt-to-Assets** stands for short-term debt over total assets, **LT Debt-to-Assets** stands for long-term debt over total assets. 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 in column 2. From column 3 to 8 we omit short term debt over total debt for collinearity issues. R-squared is the overall R^2. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Debt-to-Assets for highly indebted firms. 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. This issue might have been exacerbated by the pandemic, which predominantly affected the intangible assets of firms.

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. However, in spite of its statistical significance, the economic impact of the variable becomes relevant only for highly indebted firms (p95), while it remains below 1% of a standard deviation of Debt-to-Assets for the rest of the distribution. Misreporting in balance sheets might have a role in explaining its counterintuitive behaviour.

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 can to account for the behaviour of firms with low-to medium-debt ratios in the sample.[8] However, 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

[8] 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.

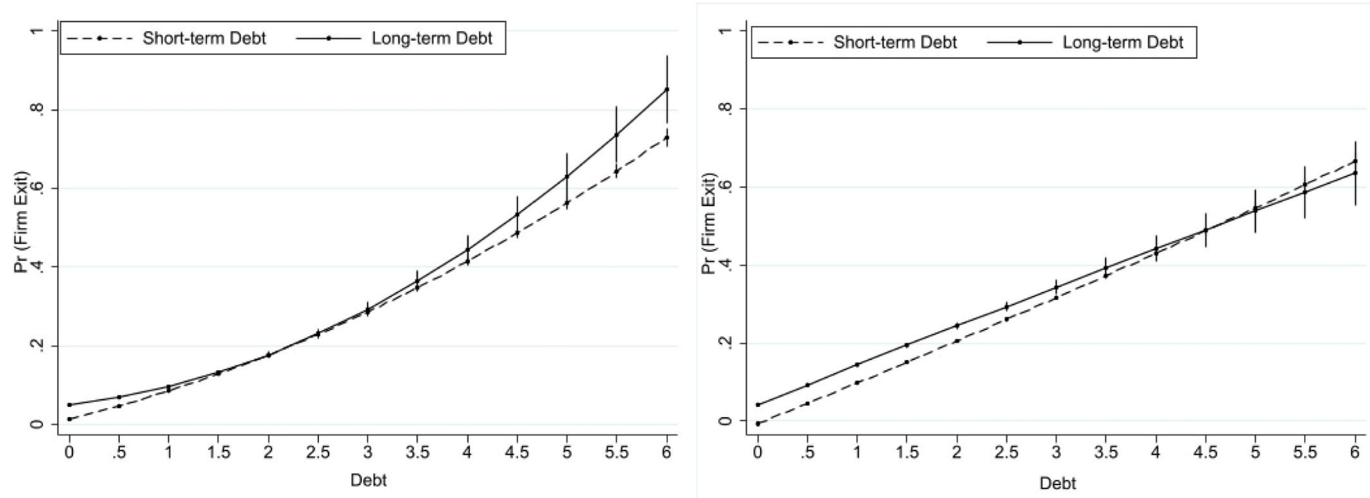


Fig. 8. Impact of short- and long-term debt on the probability of firm exit, predictive margins with 95% Confidence Intervals.
NOTES: The left-hand panel plots predictive margins calculated on the basis of the specifications of columns 4 and 6 of Table 5. The right-hand panel plots predictive margins calculated on the basis of the specification of column 8 of Table 5. Bars indicate 95 % confidence intervals. Debt levels on the x-axis, probability of firm exit on the y-axis.

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 the Italian financial environment only offering few alternatives to debt. If raising funds via equity is only feasible for big and tangible-oriented players with lower agency costs, smaller firms are first forced to collect debt and then, if the latter excessively piles up, they are not able to switch to equity and find themselves in a 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 confirms that larger firms should avoid additional piling up of debt when already in a situation of high indebtedness.

5.2. 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 which could push 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 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).

To provide a more accessible visualization of our findings, we plot predictive margins coming from the specifications of column 5 and 7 in Fig. 7. The chart indicates the probability of firm exit for each level of the debt-to-assets ratio. The Probit estimate suggests a gentler increase in the probability of firm exit for lower values of leverage. All firms ranging from the 5th to the 95th percentile show a probability of closure lower than 20%. However, moving from an average value of debt (0.7) to the 95th 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 95th 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. Results are virtually identical in case we consider merged firms as exiting the market in the year of the operation (*i.e.* assigning value 1 to the dummy firm exit in the year of the merger) or if we consider them still active in the year of the merger. Results are also confirmed when we estimate all specifications using a common number of observations. We do not report such results for brevity.

To check the robustness of previous results, we provide a number of additional exercises on firm's exit in Table 5. First, as suggested by Ugur et al. (2022), leverage may have a non-monotonic effect on financial distress events, like bankruptcy. In particular, the authors document an inverted U-shaped relationship at work, where the quadratic derives from the combination of a hazard-reducing effect of leverage, due to increased commitment, monitoring by lenders and mitigation of agency problems, and a hazard-increasing effect due to higher agency costs of debt and increased costs of service. The inverted U-shaped impact would imply some moderating effects of very high levels of debt, invalidating our previous analysis. Hence, in column 1 and 2 we augment the specifications of columns 6 and 7 of Table 4 with the inclusion of squared Debt-to-Assets. When no additional regressor is included in the model, if anything, we detect slightly explosive dynamics for very high levels of leverage (column 1). However, our results do not support any non-monotonic relationship between leverage and the probability of firm's exit when we introduce additional covariates in the specification (column 2). Squared Debt-to-Assets is negative but very small in magnitude and not significant, suggesting that a linear relationship between leverage and the probability of firm's exit must be preferred. In other words, we confirm previous results indicating that the higher firm's indebtedness, the higher its probability of closure and that no moderating effect is associated to extreme levels of debt.

Second, we distinguish between short- and long-term debt because of their different properties as disciplining devices (Huang et al., 2018; Ugur et al., 2022). We expect short-term debt to have a lower impact on firm's closure than debt with a longer maturity. We also check potential non-linearities arising from single components of debt. Columns 3 and 4 show that both short- and long-term debt-to-assets are significant predictors of firm's exit. This is confirmed when we simultaneously include the two components in the specification (column 7). As for non-monotonicity, if anything, both components show an explosive behaviour for extreme levels of leverage (columns 4 and 7). Again, we do not find evidence of an inverted U-shaped relationship between debt and firm's closure. The insignificant quadratic relationship between Debt-to-Assets and firm's exit documented in column 2 depends on the different non-linearities of short- and long-term debt that we find when both variables and their squared terms are included simultaneously (column 8). In this case, we confirm the explosive relationship between short-term debt and the probability of firm's exit, while a negative, very small and not significant negative coefficient is associated to the quadratic term of long-term debt.[9] However, the curvature implied by both squared terms is virtually null for reasonable levels of leverage, suggesting that a linear relationship is to be preferred. Indeed, in Fig. 8 we plot predictive margins with 95% confidence intervals of the relationships estimated in columns 4 and 6 (left-hand panel), and 8 (right-hand panel), respectively. The explosive dynamics of short- and long-term debt detected when the variables are included separately in the specification is evident, but only for firms with levels of debt above the 95th percentile (around 1.05 and 0.73 in the overall sample for short and long maturities, respectively). Non-linearities are negligible when both components are included in the model. As for the disciplining effect of short-term debt, we confirm that this component is less risky than debt with longer maturities. Indeed, in both panels of Fig. 8 the short-term curve lies below the long-term one. Overall, we confirm that excessive piling up of debt should be discouraged, as it generally leads to firm's closure or bankruptcy, and no moderating effect is at work for extreme levels of leverage.[10]

6. Conclusions

This paper studied the evolution of debt of Italian firms from 2010 until 2020, focusing on the aftermath of the Great 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 behavior 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 reinforces the importance of adopting a quantile approach when analyzing firm's capital structure.

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.

Declaration of Competing interest

We declare no personal interest in the matters addressed in this research paper.

Data availability

The authors do not have permission to share data.

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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 A1 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.

[9] Results from Table 5 are virtually identical when estimating all specifications over a common number of observations.

[10] Ben-Nasr et al., 2021 find evidence that the composition of debt is important in the North America context. This consideration is less relevant in the case of Italy, where the private bond market is small and most debt by firms is with banks and financial institutions.

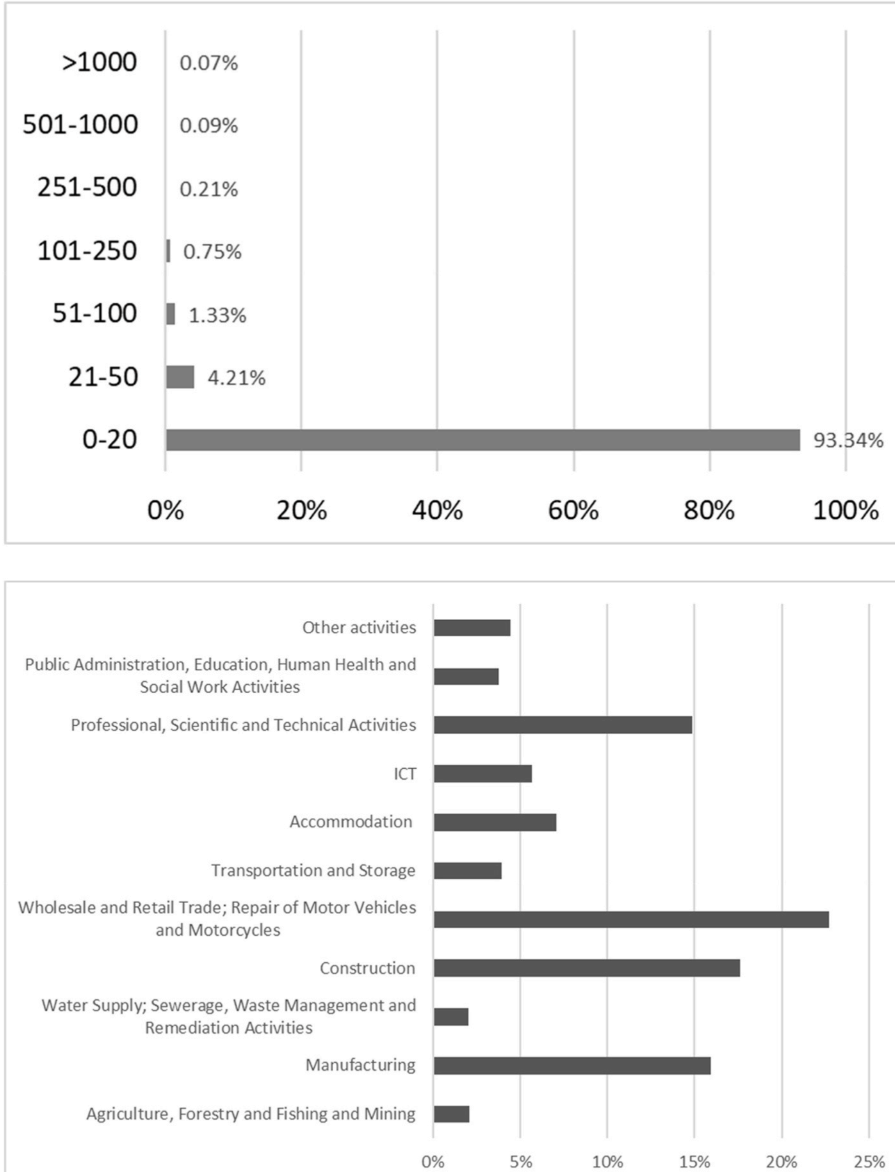

Fig. A. 1. Firms in the dataset by number of employees (top panel) and sectors (bottom panel).

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* March 25, 2020 (Ministerial Decree by the Ministry of Economic Development) the *Decreto del Presidente del Consiglio dei Ministri* April 10, 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

(*continued on next page*)

Table A 1 (*continued*)

Variable	Definition
Depreciation	Depreciation divided by total assets
Active sector	Dummy that takes value 1 if firm i belongs to a sector that was active during the pandemic according to the provisions of the DPCM April 10, 2020
Partially suspended sector	Dummy that takes value 1 if firm i belongs to a sector that was partially suspended during the pandemic according to the provisions of the DPCM April 10, 2020
Suspended sector	Dummy that takes value 1 if firm i belongs to a sector that was suspended during the pandemic according to the provisions of the DPCM April 10, 2020
Firm Exit	Dummy variable that takes value 1 if firm *i* exits the market at time *t*, 0 otherwise
ST Debt-to-Assets	Short-term debt divided by total assets
LT Debt-to-Assets	Long-term debt 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 5 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 non-debt 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 in the 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 in the 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

(continued on next page)

Table B.2 (*continued*)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(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 in the 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.

Appendix C. Potential endogeneity affecting OLS estimates

Another channel explaining the ambiguous OLS results on the determinants of firms' debt reported in section 5 might be the potential endogeneity affecting the relationship between Debt-to-Assets and its determinants. In the selection of debt's determinants, we are guided by well-grounded theoretical and empirical literature clearly indicating the direction of the nexus and its interpretation as causality. However, as robustness, we consider an estimator that directly deals with the issue. Since, potentially, all regressors used in Table 1 may be subject to endogeneity, identifying suitable external instruments is a fairly onerous task that makes Instrumental Variables estimation not a feasible option. Hence, we opt for the System GMM estimator à la Blundell and Bond (1998). The estimator is designed for panel data that have many units of observations (N) and few time periods (T); it copes with dynamic linear relationships that involve not strictly exogenous regressors, and fixed individual effects. Importantly, it is designed for the implementation of internal instruments, *i.e.* lags of the instrumented regressors. As such, it perfectly suits our needs. In System GMM the first-differenced equation is added to the original one in levels, so that they are estimated in a system. Predetermined and endogenous variables in levels are instrumented with lags of their own first differences. Thanks to the additional orthogonality conditions, System GMM achieves gains in terms of asymptotic efficiency over the traditional difference GMM estimator by Arellano and Bond (1991).

In Table C1 we present our findings, replicating the two main specifications of Table 1.To avoid instruments proliferation, that by overfitting the endogenous regressors might fail to remove their endogenous components and is associated with a number of shortcomings (finite sample bias, increases in false positive and implausible values of specification tests), we follow Roodman (2009) and collapse the instrument matrix in each specification. We also require robust standard errors. In columns 1 and 2 we use all available lags of each regressor as instruments for the first differenced equation. Then, in columns 3 and 4 and 5 and 6 we limit the number of lags to the most recent four and three, respectively. The procedure does not seem to clarify the ambiguous OLS results presented in section 5. *Employment* and *Sales* are still negative, contrary to common corporate finance theory. Also *Tangibility* reports again a counterintuitive negative and significant coefficient, as in section 5. Moreover, while *ΔSales* still shows a negative and significant coefficient, as expected, *ΔAssets* turns now positive. Finally, both *Depreciation* and *Ebitda* still do not show any explanatory power. Overall, the estimation confirms OLS results in section 5 hence does not prove useful in explaining the counterintuitive behaviour of most regressors. Moreover, the AR (2) test and the Hansen J-test cast some doubt on the feasibility of the procedure.

Since the presence of second order autocorrelated disturbances in the first differenced equations might bias results, in Table C2 we replicate the same specifications but we start using the fourth lag of each variable as instrument.[11] *ΔAssets* now turns back to its negative and significant coefficient. However, the other counterintuitive results do not change, and the Hansen J-test is still problematic. Similar results emerge from difference GMM estimations and if we collapse our sample in two- and three-years average, a common approach when applying GMM. In any case, the implementation of a procedure that deals with endogeneity does not prove useful in explaining the ambiguous results discussed in section 5 and other strategies must be preferable.

Table C.1
Determinants of leverage, Sys-GMM regressions.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Debt-to-Assets (t-1)	1.003***	0.945***	1.003***	0.945***	1.003***	0.943***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Employment (t-1)	−0.034***		−0.036***		−0.037***	
	(0.009)		(0.011)		(0.012)	
Ebitda (t-1)	0.000	0.001	0.000	0.001	0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Tangibility (t-1)	−0.440***	−0.397***	−0.443***	−0.400***	−0.436***	−0.396***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
ΔAssets	0.010***		0.010***		0.011***	
	(0.001)		(0.001)		(0.001)	
Depreciation (t-1)	−0.000	−0.000	−0.000	−0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sales (ln, t-1)		−0.046***		−0.046***		−0.047***
		(0.000)		(0.000)		(0.000)
ΔSales		−0.029***		−0.030***		−0.030***
		(0.000)		(0.000)		(0.000)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of instruments	68	68	39	39	33	33
Prob > AR(2)	0.000	0.000	0.000	0.000	0.000	0.000
Prob > Hansen	0.000	0.000	0.000	0.000	0.000	0.000
Observations	6,117,297	6,260,975	6,117,297	6,260,975	6,117,297	6,260,975

Estimation method: Sys-GMM. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. The instrument matrix is collapsed. All regressors are treated as endogenous. Column 1, 2 all available lags as instruments for the first difference equation. Column 3, 4 use four lags of each variable as instruments for the first difference equation. Column 5, 6 use the three most recent lags as instruments. First differences of lagged regressors are used as instruments for the level equation. AR(2) tests for second order autocorrelated disturbances in the first differenced equations. Prob > AR(2) reports its p-value. The Hansen J-test tests the null hypothesis of instrument validity. Prob > Hansen reports its p-value. Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Table C.2
Determinants of leverage, Sys-GMM regressions.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Debt-to-Assets (t-1)	1.000***	0.999***	0.998***	1.001***	0.996***	0.998***
	(0.009)	(0.005)	(0.011)	(0.006)	(0.012)	(0.005)
Employment (t-1)	0.004		0.004		0.004	
	(0.006)		(0.006)		(0.006)	
Ebitda (t-1)	−0.001	−0.003	0.000	−0.004	0.004	−0.145
	(0.002)	(0.004)	(0.001)	(0.005)	(0.015)	(0.108)
Tangibility (t-1)	0.015	−0.098***	0.014	−0.099***	0.015	−0.068***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.017)	(0.025)
ΔAssets	−0.365***		−0.372***		−0.379***	
	(0.012)		(0.014)		(0.015)	
Depreciation (t-1)	−0.665**	0.348*	−0.720**	0.414	−0.774*	0.201
	(0.286)	(0.208)	(0.346)	(0.254)	(0.413)	(0.208)
Sales (ln, t-1)		−0.027***		−0.026***		−0.021***
		(0.001)		(0.001)		(0.004)
ΔSales		−0.127***		−0.124***		−0.115***
		(0.002)		(0.003)		(0.007)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of instruments	45	45	39	39	33	33
Prob > AR(4)	0.446	−0.404	0.481	−0.419	0.492	−1.026
Prob > Hansen	0.000	0.000	0.000	0.000	0.000	0.000
Observations	6,117,297	6,260,975	6,117,297	6,260,975	6,117,297	6,260,975

Estimation method: Sys-GMM. Dependent variable: Debt/Tot. Assets. See Appendix A. for variables' definitions. The instrument matrix is collapsed. All regressors are treated as endogenous. Column 1, 2 all available lags as instruments for the first difference equation. Column 3, 4 use from four to six lags of each variable as instruments for the first difference equation. Column 5, 6 use from four to five lags as instruments. First differences of lagged regressors are used as instruments for the level equation. AR(4) tests for fourth order autocorrelated disturbances in the first differenced equations. Prob > AR(4) reports its p-value. The Hansen J-test tests the null hypothesis of instrument validity. Prob > Hansen reports its p-value. Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

[11] Since we also detect the presence of third order autocorrelated disturbances in the first differenced equations we move to using the fourth lag of each variable as starting lag for the instruments.

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