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On the determinants of corporate default in the EU-27

Evidence from a large sample of companies

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Contents

Abstract

We analyze a large sample of companies operating in the EU-27 in the period 2007-2018 to gain new insights on the determinants of corporate defaults. The sample includes micro, small, medium and large enterprises, both active and defaulting. We document significant differences in the drivers of insolvency across firm size categories. Micro and small firms are significantly more vulnerable to sectoral shocks and to disruptions along the supply chain than larger companies. Instead, the default probability for all firms is significantly larger when companies experience in the previous year negative end-of-the year equity, that is a measure of prolonged financial distress. By exploiting institutional differences in judicial efficiency among EU-27 countries, we find financial distress is more likely to predict default in jurisdictions with more efficient insolvency procedures. Finally, we derive potential implications of our findings, especially with regard to the recent crises hitting European firms and the harmonisation of national insolvency regimes in the EU-27 towards most efficient legal practices, as foreseen under the Capital Markets Union Action Plan.

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Executive Summary

In this report we study the determinants of corporate bankruptcy using a large sample of companies from the EU-27 in the period 2007-2018. Our sample comprises companies of all sizes, including micro firms (i.e., enterprises with less than 10 employees and at most 2 million euros of total assets), which are usually disregarded in similar empirical analyses. Micro firms are relevant from an economic and a social point of view, however. Indeed, they account for about 90% of companies in the EU-27, with a large representation in all European countries. Second, micro firms are, on average, younger and more financially fragile, that is they are more leveraged and less profitable than larger enterprises. As a consequence, they are unconditionally more likely to default. The results from a linear probability model highlight that, keeping relevant firm characteristics constant, corporate default is strongly predicted by country-sector bankruptcy waves. The conclusions are robust with respect to unobserved heterogeneity at the country and industry levels, as well as to common shocks. These findings support the notion that industry dynamics are crucial in predicting corporate bankruptcy. We additionally find that micro firms display a significantly greater sensitivity to the bankruptcy rate in their sector with respect to larger companies, even when compared to SMEs. We also develop a measure for bankruptcy waves at supply-chain level rather than at the level of the downstream market where each firm operates, and explore the incidence of this variable in the default prediction model. We find that corporate defaults are more likely to occur in presence of supply chain disruptions, again especially for smaller firms. The strong and significant impact of sectoral dynamics on the solvency of individual firms that we uncover has important implications, particularly in the light of the Covid-19 shock. Specifically, they lend support to the hypothesis of a "firm exit multiplier" proposed by the recent macroeconomic literature to capture the amplified number of bankruptcies caused by some initial defaults. While they are inherently different in nature, both the Covid-19

and the energy crises are leaving behind a legacy of highly indebted and financially vulnerable firms at the global level. The spread of the pandemic and subsequent containment measures induced a sudden reduction in annual cash flows and profitability in the corporate sector. The more recent energy crisis has brought about a marked and unexpected increase in the production costs. In both cases, the end result is the occurrence of short-run losses that might, if large and persistent enough, weigh on firms' liquidity and solvency. This outcome is more likely to occur if firms have insufficient pre-crisis levels of capital to absorb the shocks, like it is usually the case for micro and small ones. Negative end-of-the year equity is not a rare event: the share of companies with negative equity in our sample is around 20%, on average. Not surprisingly, this occurs predominantly among micro firms, which are highly levered. When controlling for other relevant determinants of bankruptcy, the empirical findings from our econometric model confirm that our measure of financial distress is an important predictor of corporate default, particularly for micro and small companies. While a large wave of corporate bankruptcies has not occurred so far in the aftermath of the Covid-19 shock, our results suggest that significant risks are still looming over the economy. Specifically, the legacy of the pandemic in terms of corporate financial fragility might eventually deteriorate into insolvencies in the medium run. Since micro companies operate in more labour-intensive sectors, our results are also suggestive of important social costs following the layoffs that will likely accompany insolvencies. In the second part of the report, we assess the role played by country-level institutional quality in driving the observed corporate default dynamics. In particular, we exploit cross-sectional heterogeneity across the EU-27 member States according to their level of judicial efficiency. We focus on two dimensions of national bankruptcy frameworks: i) the time of insolvency proceedings, that is the length for creditors to recover their credit through reorganization, liquidation or debt enforcement (foreclosure or receivership) proceedings; and ii) the recovery rate upon insolvencies, that is how many cents on the dollar claimants recover from an insolvent firm. We find that companies that face sectoral shocks (either at downstream market or at the supply-chain level) and in financial distress are more likely to default in countries that display more efficient legal systems as measured by the time taken to resolve insolvencies. By contrast, distressed firms in less efficient jurisdictions are more likely to survive in the short run. Furthermore, the descriptive analysis shows that firms operating in countries with more efficient insolvency regimes are larger and more profitable, suggesting that the short run increase in bankruptcy ultimately improves resource allocation and productivity over the medium and longer term. These findings are suggestive of significant beneficial effect to be derived from the harmonisation of national insolvency codes across EU member states towards more efficient levels, as foreseen under the Capital Markets Union Plan. We also investigate potential differences in these findings across firm size classes. We find that the combined effect of sectoral shocks with judicial efficiency is mostly driven by SMEs and large companies and, to a less extent, by micro firms. By contrast, the interplay between judicial efficiency and financial distress is particularly relevant for micro firms. These results point again to the need to duly account for heterogeneity when it comes to the determinants of corporate default across firm size categories.

1 Introduction

We study the determinants of corporate default for companies operating in the EU-27 in the period 2007-2018. We assemble a large sample of companies that are actively operating, as well as enterprises in financial distress and those in default status. Our sample comprises companies of all sizes, including micro firms (i.e., enterprises with less than 10 employees and at most 2 million euros of total assets), which are usually disregarded in similar empirical analyses. [1] We argue that analysing firm insolvency also from the perspective of micro enterprises is important, for at least two reasons. First, micro firms are relevant from an economic and a social point of view. Indeed, they account for about 90% of companies in the EU-27, with a large representation in all European countries. Second, micro firms are, on average, younger and more financially fragile, that is they are more leveraged and less profitable than larger enterprises. As a consequence, they are unconditionally more likely to default. After providing a comprehensive descriptive analysis of micro firms in the EU-27 over more than a decade spanning the period 2007-2018, the first contribution of this paper is to study the determinants of their default, also in comparison with small, medium and large European firms. In the empirical analysis, we refer to the default model developed by Beaver *et al.* (2019) and investigate the determinants of corporate default disentangling the impacts of firm-level variables - such as profitability, book leverage, earning before taxes and interest (over total liabilities), company size (as measured by the log of total assets) - as well as aggregate factors, notably the sector bankruptcy rate (i.e., the proportion of firms filing for bankruptcy in each sector-country-year). The results from a linear probability model highlight that, keeping the relevant firm characteristics constant, corporate default is strongly predicted by country-sector bankruptcy waves. The conclusions are robust with respect to unobserved heterogeneity at the country and industry levels, as well as to common shocks over time. These findings support the no-

[1] Few works pursue a similar direction in their analysis focusing on small firms (Sakai *et al.*, 2010; Kim *et al.*, 2015), but with country specific samples (Korea and Japan, respectively).

tion that industry dynamics are crucial in predicting corporate bankruptcy, in line with previous findings in the literature (see, e.g., Chava and Jarrow, 2004). We additionally find that micro firms display a significantly greater sensitivity to the bankruptcy rate in their sector with respect to larger companies, even when compared to SMEs. We also develop a measure for bankruptcy waves at supply-chain level rather than at the level of the downstream market where each firm operates, and explore the incidence of this variable in the default prediction model. Using this alternative variable, we robustly find that corporate defaults are more likely to occur in presence of supply chain disruptions, again especially for smaller firms. These results are robust across different specifications and to the inclusion of additional controls to the original model by Beaver *et al.* (2019).[2] The strong and significant impact of sectoral dynamics on the solvency of individual firms that we uncover has important implications, particularly in the light of the Covid-19 shock, which propagated unevenly across sector leading to substantial reallocation (Barrero *et al.*, 2021). In a similar vein, when modelling the Covid-19 crisis in a macroeconomic framework, Bilbiie and Melitz (2020) and Guerrieri *et al.* (2020) introduce the concept of "firm exit multiplier" to capture the amplification of the number of bankruptcies caused by some initial defaults. While it is empirically hard to identify such causal relationship at the micro level, in quantifying individual firms' sensitivity to sectoral shock and supply-chain disruption, our estimates provide a useful indication in that direction.

While they are inherently different in nature, both the Covid and the energy crises are leaving behind a legacy of highly indebted and financially vulnerable firms at the global level. The spread of the pandemic and subsequent containment measures induced a sudden reduction in annual cash flows and profitability in the corporate sector. The more recent energy crisis has brought about a marked and unexpected increase in the production costs. In both cases, the end result is the occurrence of short-run losses that might, if large and persistent enough, weigh on firms' liquidity and

[2]Our results are robust to a different estimation strategy based on non-linear probability models (i.e., logit).

solvency. This outcome is more likely to occur if firms have insufficient pre-crisis levels of capital to absorb the shocks, like it is usually the case for micro and small ones. To shed light on this issue, we explicitly examine the role of financial distress as a predictor for corporate default. Formally, we augment the predictive model by Beaver *et al.* (2019) with an indicator for negative end-of-the-year equity as reported in the balance sheet. We do that for a twofold reason. First, from a legal perspective, solvency issues arise when equity falls below defined thresholds or becomes even negative. In such an event, the firm can either opt to replenish capital or to file for bankruptcy. Negative end-of-the year equity is not a rare event: the share of companies with negative equity in our sample is around 20%, on average. Not surprisingly, end-of-year negative equity occurs predominantly among micro firms, which are highly leveraged. Second, financial distress is a situation that may characterize many European companies in the recent years, as discussed above.

Against this backdrop, our empirical findings that financial distress, measured by the occurrence of negative equity, is an important determinant of corporate default especially for micro and small companies provide an important warning on the medium term evolution of corporate financial fragility.[3]

Next, we assess the role played by country-level institutional quality in driving the observed default dynamics. In particular, we exploit cross-sectional heterogeneity across the EU-27 member States according to their level of judicial efficiency. An extensive literature has documented the importance of creditors' rights and enforcement procedures (Porta *et al.*, 1998; Davydenko and Franks, 2008; Djankov *et al.*, 2008), and few works relate these institutional factors specifically to bankruptcy (Claessens and Klapper, 2005; Davydenko and Franks, 2008). We focus on two dimensions of national bankruptcy frameworks: i) the time of insolvency proceedings, that is the length for creditors to recover their credit through reorganization, liquidation or debt

[3]This result is in line with Orlando and Rodano (2020) who analyze a large sample of Italian companies and find that under-capitalization is a good predictor of corporate insolvency and of firm dissolution.

enforcement (foreclosure or receivership) proceedings; and ii) the recovery rate upon insolvencies, that is how many cents on the dollar claimants recover from an insolvent firm. The source of data on legal institutions is the Doing Business database by the World Bank.[4] We find that companies that face sectoral shocks (either at downstream market or at the supply-chain level) and in financial distress are more likely to default in countries that display more efficient legal systems as measured by the time taken to resolve insolvencies. By contrast, distressed firms in less efficient jurisdictions are more likely to survive in the short run.

We also investigate potential differences in these findings across firm size classes. We find that the combined effect of sectoral shocks with judicial efficiency is mostly driven by SMEs and large companies and, to a less extent, by micro firms. By contrast, the interplay between judicial efficiency and financial distress is particularly relevant for micro firms. These results point again to the need to make a distinction between firms of different size categories, and specifically to analyse micro firms separately from larger companies when it comes to the determinants of corporate default.

With these set of results, we contribute to the literature that analyzes cross-country differences in corporate profitability and insolvency as a mechanism to bring about an efficient allocation of financial resources in the economy. We also deliver some policy implications, especially in the context of the recent Covid-19 crisis, although our sample period ends in 2018. Indeed, while it has materialised as a large shock propagating asymmetrically to different sectors, the Covid-19 crisis has brought about a sharp decline in corporate revenues and cash flows across the board. In the presence of significant fixed costs of production, the revenue shortfall has ultimately resulted in financial distress. This dynamics have been predicted for instance by Carletti *et al.* (2020) using Italian data or by Garcia and Ho (2021) using a sample of French firms. While a large wave of corporate bankruptcies has not occurred so far (Wang *et al.*, 2020; Djankov and Zhang, 2021), our results suggest that, in the absence of *ad hoc* policy in-

[4]https://www.doingbusiness.org/en/data/exploretopics/resolving-insolvency

terventions, significant risks are still looming over the economy, and the sectors most hardly hit by the Covid-19 crisis in particular. Specifically, the legacy of the pandemic in terms of corporate financial fragility might eventually deteriorate into insolvencies in the medium run, as emphasised also by recent findings in the literature (Banerjee *et al.*, 2020a; Gourinchas *et al.*, 2020). We contribute to this debate by bringing new evidence that a bankruptcy wave could be expected especially among micro firms, that are more financially vulnerable, and in the countries characterised by relatively more efficient judicial systems. By documenting that micro companies operate in more labor-intensive sectors, our results are also suggestive of important social costs following the layoffs that will likely accompany insolvencies.

While in the short run corporate insolvencies come at a cost, from both an economic and a social standpoint, they also act as an important cleansing mechanism for the economy over the medium and longer term. In our results, companies in financial distress are more likely to default in countries that display relatively more efficient legal systems. These countries also display a larger share of medium-sized and large companies and, on average, a smaller share of companies with negative profits and in financial distress, a result that is consistent with the evidence by Favara *et al.* (2017). By minimizing time and costs for liquidating ailing firms, a well-functioning insolvency framework ultimately enables an efficient reallocation of resources towards viable companies and new entrants, allowing them to grow bigger and gain market shares, and ultimately laying the ground for macroeconomic growth. In countries with less efficient bankruptcy codes, the survival of less efficient and non-viable firms acts as a drag on the economy. Indeed, Davydenko and Franks (2008) find that country-level bankruptcy codes matter for the allocation of capital and, in turn, affect average productivity.

Similar to the argument by Cirmizi *et al.* (2012), who discusses the role of efficient bankruptcy laws in the wake of the 2008 financial crisis, a potential policy implication of our findings is that the EU-27 could benefit from the harmonisation of national insolvency codes across countries towards more efficient levels, as foreseen under the Capital Markets Union Plan. A reform in this direction may, in fact, imply larger defaults in the short-run due to the legacy of the Covid-19 crisis, but might improve capital allocation efficiency and lead to a reduction in the number of "zombie" firms in Europe in the longer run. Indeed zombie firms reduce aggregate productivity (Adalet McGowan *et al.*, 2018) and slow recovery (Acharya *et al.*, 2019); the share of zombie firms has surged in the aftermath of the global financial crisis (Banerjee and Hofmann, 2020), and will likely characterize also the post-pandemic years (Banerjee *et al.*, 2020b), especially in the absence of policy action to reduce the risk of zombification (Laeven *et al.*, 2020). This argument is further corroborated, in a long run historical perspective based on evidence from 17 countries over 150 years, by Jordà *et al.* (2020), who find that recessions are deeper and longer in countries where institutions are less efficient in corporate restructuring and liquidating insolvent companies, because of the persistent effects of debt overhang for the aggregate economy.

The rest of the paper is organized as follows. Section 2 describes our data and summary statistics. Section 3 presents our baseline empirical results, and a series of tests that exploit cross-country heterogeneity within EU-27. Section 4 concludes.

2 Data description and empirical analysis

To build our sample, we rely on the firm-level data from the Orbis database provided by Moody's Bureau Van Dijk. Specifically, we assemble a large sample of non-financial companies for which information on the status of activity is reported.[5] We initially select all companies for which key balance sheet items (total assets, total liabilities, profits before taxes and financial expenses, financial expenses) are not missing. Following Kalemli-Ozcan *et al.* (2015), then, for each company, we retain unconsolidated

[5] In Orbis, the variable "status" broadly takes the following values: Active, Dissolved, In liquidation, Inactive, Bankruptcy, plus some rare hybrid cases like Active (default of payments), Active (dormant), Unknown.

accounts (U1 or U2), and consolidated accounts (C1) when unconsolidated accounts are not available.[6] The final sample comprises about 58 million observations over the period 2007-2018. The panel is reasonably balanced over the sample period, with the cross-sectional coverage becoming more stable as from 2011.[7]

2.1 Empirical approach

Corporate default has been extensively studied in the literature. The seminal contribution of Altman (1968) has been replicated in different contexts (Claessens *et al.*, 2003; Altman *et al.*, 2017), and further extended in more recent papers (see, e.g., Chava and Jarrow (2004); Bonfim (2009); Bauer and Agarwal (2014)).

We follow the recent contribution by Beaver *et al.* (2019) and implement the following model to predict firm bankruptcy:

$$Pr[Fail_{i,t+1} = 1] = G(X^{t}_{i,t}\gamma + \alpha_s + \alpha_c + \alpha_t), \tag{1}$$

where the subscript i refers to the firm and t to time. Our dependent variable , $Pr[Fail_{i,t+1} = 1]$, is modelled as a dichotomous indicator which takes the value of 1 for a bankrupt firm in year $t+1$, and 0 otherwise. We consider a firm bankrupt, or in default, when its status is recorded either as "Dissolved" or "In liquidation" or "Inactive" or "Bankruptcy" or "Insolvency proceedings" in Orbis. X^{t} is a vector of independent variables. The set of variables includes time-varying firm characteristics which are associated to the probability of bankruptcy. $Negative\ ROA_{i,t}$ is a dummy variable equal to one if the return on assets ($ROA_{i,t}$) is negative, 0 otherwise. $ROA_{i,t}$ is the net income over total assets. $LTA_{i,t}$ is the ratio of total liabilities over total assets. $Financial\ expenses_{i,t}$ is the ratio of financial expenses to total liabilities. $SIZE_{i,t}$ is the natural logarithm of the firm's total assets. $Sector\ Bankrate_{s,c,t}$ is the bankruptcy rate

[6]Some firms have duplicate reports within a year. In those cases, we keep only the records that closer to the latest accounting record in each given year.

[7]Key variables derived from income statements and balance sheets have been winsorized at the 5%-95% level.

of sector s and country c at time t. As an alternative measure for sectoral-level shocks, we define *Supply Chain disruption*$_{s,c,t}$, that is the weighted average of bankruptcies occurring in the sectors belonging to the supply chain of each sector s and country c at time t; the weights are determined using the relative amount of flow of trades in the supply chain of each downstream sector contained in the OECD harmonised national Input-Output tables.[8]

Theoretical arguments and empirical results in the literature suggest that non-profitable firms usually display a higher probability of bankruptcy. Hence, we expect a positive coefficient for $NROA_{i,t}$ and negative one for both $ROA_{i,t}$ and $ETL_{i,t}$. Moreover, bankruptcy is expected to increase with higher leverage ($LTA_{i,t}$) and for smaller firms ($SIZE_{i,t}$) and during bankruptcy waves that occur at country-sector-year level. The model includes sector fixed effects ($alpha_s$), country fixed effects ($alpha_c$), and year fixed effects ($alpha_t$). By including these fixed effects, the model allows us to quantify the impact of sectoral-country-time default patterns and firm specific characteristics, while controlling for sector and country time invariant differences, and for time effects common to all companies in our sample. Further, to control for heteroscedasticity and potential correlation in the error terms, we use robust standard errors in all specifications.

The function $G(.)$ in equation (1) is a probability distribution function, which we assume to be linear in its parameters. Thus, estimates presented in the next sections are obtained running a linear probability model.[9]

To gauge potential differences in the sensitivity of bankruptcy to its determinants across firm size classes, we split the sample of firms in four groups according to their dimension: micro, small, medium and large firms. The classification of companies is the one adopted by the European Commission. Then, we run the model in Equation

[8] *https : //stats.oecd.org/Index.aspx?DataSetCode = IOTS*2021

[9] This strategy has been preferred due to the presence of fixed effects, and the large number of observations. Our estimates are robust to the assumption of a logistic function, thus using a logit model. Baseline results using logit estimates are available in the Appendix.

(1) also on the four subsamples.[10]

2.2 Sample description

Table 1 shows summary statistics, from the whole sample of firms, as well as for the different size categories, notably micro, small, medium and large enterprises. The micro firms in our sample display, on average, 5 employees and significantly lower total assets than firms in other categories. Small firms have on average 34 employees, while medium and large companies 141 and 1089 employees, respectively. Micro firms are also significantly younger, with an average level of years of activity of about 17 years, against 24 years of small firms and more than 25 years for the two larger groups. Micro firms are also markedly leveraged, with an average ratio of liabilities over total assets (*LTA*) of about 82%. The ratio ranges between 68% and 64% for larger companies.[11] Micro firms are also less profitable than larger firms. In fact, thei average ROA is negative, because of the large fraction of companies registering negative profits during the sample period (around of 37%). This figure squares with the frequency of firms in financial distress. We classify a company in distress if the end-of-the-year value of shareholder funds is negative.[12] Distressed companies, in other words, are defined as those that have a level of total liabilities that exceeds the book value of total assets. The fraction of distressed companies among micro firms is 21%, a percentage that is roughly three times as larger as that for SMEs and large companies (around 8-7%). We also compute the proportion of firms filing for bankruptcy in the sector-country-year where each firm operates and for bankruptcy waves occurring within the supply chain in each sector-country-year. The variables are labeled *Sector Bankrate* and *Supply*

[10]The classification is available at $https://ec.europa.eu/growth/smes/sme - definition_en$ and is based on average values of total assets, turnover and employees of each firm observed in the period of analysis.

[11]The very high level of financial leverage of micro companies in Europe is arguably related to the low levels of minimum capital requirements in many European countries. For instance, in Italy the minimum capital for a limited liability company is 10,000 euros; in Spain this threshold is 3,000 euros. In some countries, under some special and simplified regimes, the minimum capital requirements might even be reduced to 1 euro (the "Socie´te´ par actions simplifie´e - Sas" in France is an example).

[12]This variable is available in Orbis.

Chain Disruption, respectively. By construction, these variables do not change at the level of the single company. Bankruptcy rates at sectoral or supply chain levels are, on average, rather stable across the four size-category groups. Micro firms are more financially fragile than larger companies, as documented by the variable *Distress*. There are arguably different reasons for that. First, since firm status is time-varying, the high frequency of distress among smaller enterprises could simply be the result of ailing firms progressively shrinking over time, before default. Second, given that size is inversely correlated with firm age, micro firms are more likely to be at the initial stages of their activities (e.g., start-ups), when profitability can easily turn negative.

Table 1: Summary statistics by size group: EU-27 (2007-2018)

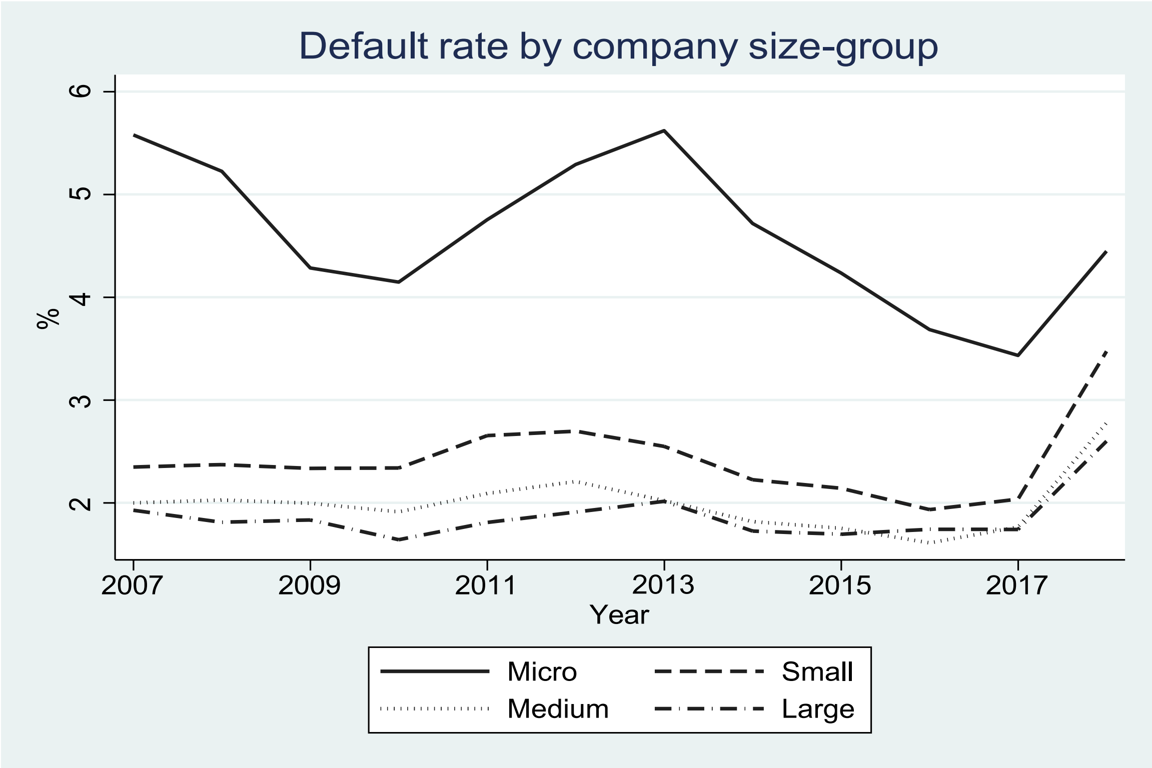
	Micro	**Small**	**Medium**	**Large**
Fail	0.05	0.02	0.02	0.02
Distress	0.21	0.08	0.07	0.07
ROA	-0.00	0.03	0.02	0.02
Negative ROA	0.37	0.26	0.27	0.29
LTA	0.82	0.68	0.67	0.64
Financial expenses	0.02	0.02	0.03	0.03
Log(TA)	11.71	14.84	15.54	15.59
Number of employees	5.03	34.27	140.64	1089.05
Sector Bankrate	0.05	0.04	0.04	0.04
Supply chain disruption	0.04	0.04	0.04	0.04
Cash over TA	0.22	0.12	0.09	0.07
Age	16.72	23.54	25.75	25.19
Observations	50761800	5859591	1419558	374984

Source: Own elaboration.

As a result of being more financially vulnerable, micro firms are also unconditionally more likely to enter into default status.[13] Figure 1 plots the yearly default rate for micro, small, medium and large companies in the EU-27 over the period 2007-2018. The average default rate of micro firms hovers around 5%, with peaks around 6% in the years around the great financial crisis and the sovereign debt crisis. SMEs and large firms have comparable levels of default rates (around 2% on average), with also similar time dynamics.

[13]Using Orbis data, we define the default year for a company when the status of the firm is recorded either "Dissolved" or "In liquidation" or "Inactive" or "Bankruptcy" or "Insolvency proceedings" and for the latest year when financial accounting data have been reported.

Figure 1: EU-27 in the years 2007-2018



Micro firms are not only more likely to default, but are also relevant from a macroeconomic point of view. Indeed, they account for about 90% of companies in the EU-27, with a large representation in practically all European countries (Figure 2). The smaller share of micro firms recorded in countries such as Austria, Germany, Luxembourg and the Netherlands is likely to be attributed to the limited representativeness of the Orbis data for such size categories in these countries (see Kalemli-Ozcan *et al.* (2015) for a detailed discussion on this issue) due to their law requirements for filing financial statements.

Figure 2: Share of companies by size-group in the EU-27

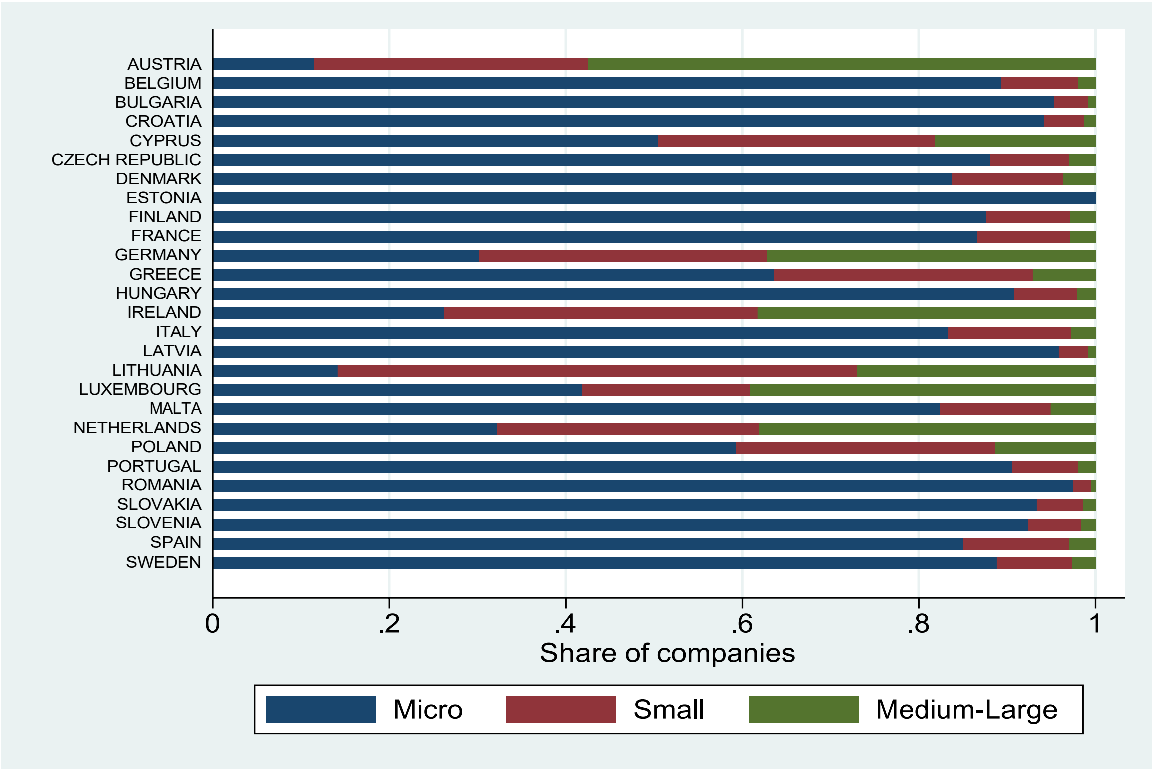


Figure 3 displays the distribution of firm size categories across macro-sectors. Micro firms account for a significant share of companies in all sectors of the economy, particularly in labour-intensive sectors (e.g., education, health and services), while they are under-represented in capital-intensive sectors (e.g., industry sector). Despite their large number, micro firms account for a relatively small share of total employees (about 20%). Naturally, as Figure 4 shows, their employment share is relatively large in labor-intensive sectors (e.g., they account for more than 40% of total employees in the services sector, like hotel and restaurants).

Figure 3: Share of companies by industry in the EU-27

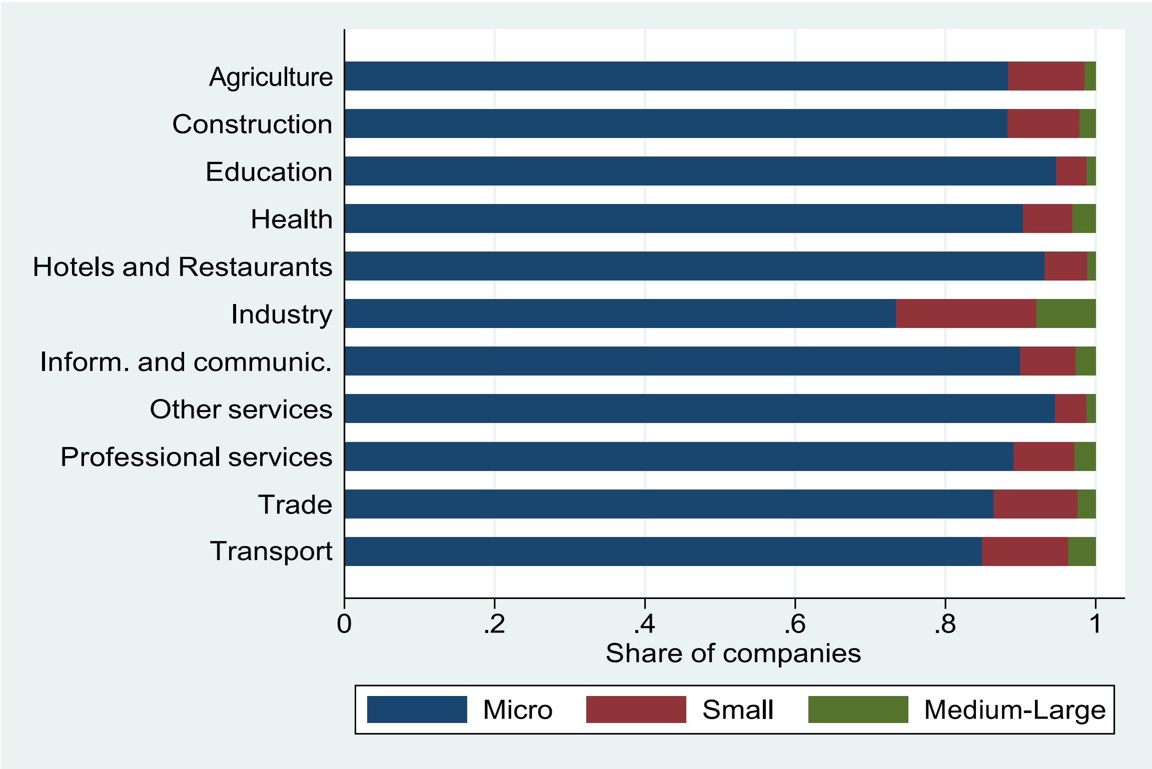


Figure 4: Share of employees by company size-group in the EU-27

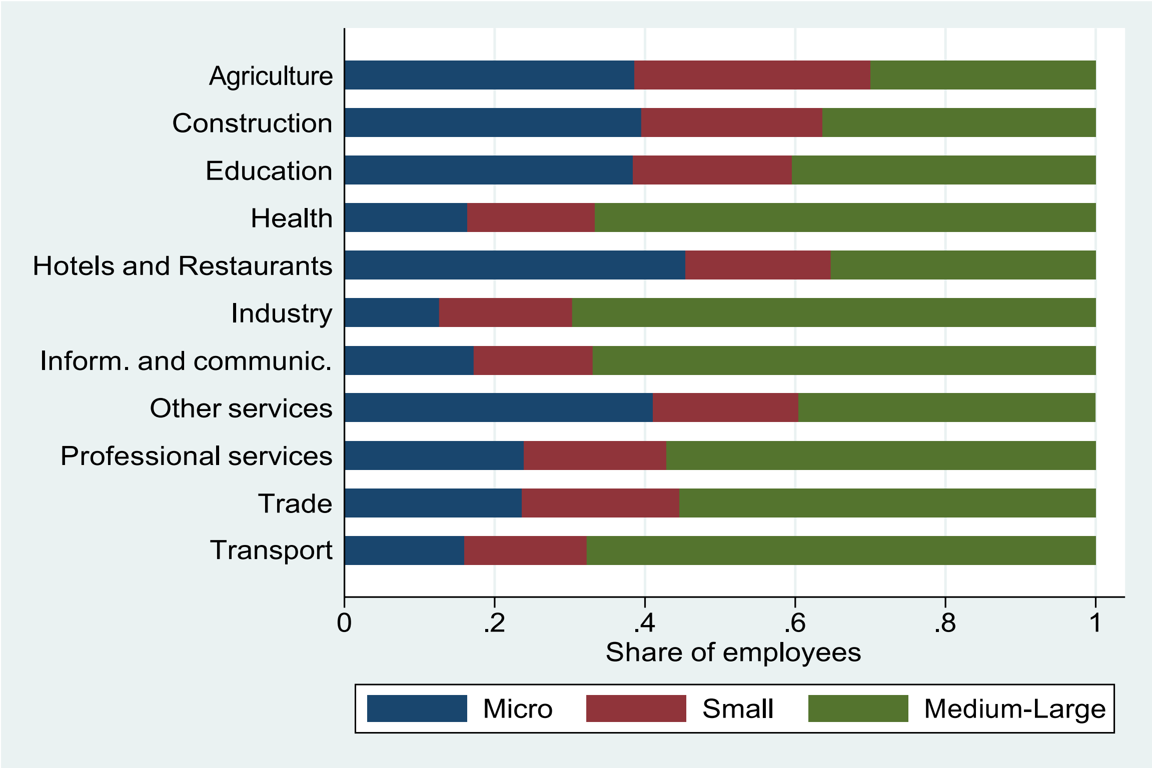


Table 2 presents the sample summary statistics. In column 1 of Table 2 we display summary statistics for the full sample of companies, while in column 2 we consider only active companies, and companies in default in column 3. On average, firms in default show negative end-of-the year profits and negative ROA. This is in line with the average low level of earnings before taxes and interests over total liabilities, which is well below the values for active firms. The average values of *Sector Bankrate* and *Supply Chain disruption* are significantly larger in the subgroups of companies in default. This indicates that there is a correlation between bankruptcy waves emerging within a country-sector-year and the occurrence of bankruptcy at the level of the individual firm. In the empirical analysis, we formally test if this unconditional correlation holds also when conditioning on other observable characteristics, and when considering firms in different size categories separately.

In further tests, we examine how national bankruptcy regimes affect the probability of firms becoming insolvent. To do so, we complement our company data with information on the institutional framework for resolving financial distress and dealing with corporate insolvency drawn from the World Bank - Doing Business Project. In particular, we focus on two specific dimensions: judicial efficiency, measured by the speed of resolving insolvency, and the recovery rate upon insolvency. These aspects of bankruptcy regimes vary considerably across countries and over time. In our sample of EU-27 countries, the average number of years to resolve insolvency is 2.16, with a standard deviation of 1.23. The average recovery rate is around 59%, again with significant cross-sectional variability (the standard deviation is equal to 21.7%).

Table 2: Summary statistics by default status: EU-27 (2007-2018)

	Entire sample	**No default**	**Default**
Fail	0.04	0.00	1.00
Distress	0.19	0.18	0.41
ROA	0.00	0.01	-0.12
Negative ROA	0.35	0.34	0.58
LTA	0.80	0.79	1.14
Financial expenses	0.02	0.02	0.02
Log(TA)	12.15	12.19	11.15
Number of employees	19.62	19.98	9.59
Sector Bankrate	0.05	0.04	0.09
Supply chain disruption	0.04	0.04	0.05
Cash over TA	0.21	0.20	0.23
Age	17.69	17.77	15.81
Observations	58415933	55899055	2516878

Source: Own elaboration.

3 Empirical analysis

3.1 Results

Table 3 reports estimates of the corporate default model for the full sample. In model 1 we include firm-specific variables, as well as year, country and sector fixed effects. The coefficient of *Negative ROA* is positive and statistically significant, indicating that negative profitability is an important determinant of future default. At the same time, *ROA* has a negative coefficient, which does not reach significance, however. The coefficients for *LTA* and *Financial expenses* are both positive and statistically significant, suggesting that firms that are more leveraged and that incur higher financial expenditures are more likely to default. As expected, firm size is negatively correlated with the default probability: larger companies are less likely to go bankrupt. The coefficient of *Sector Bankrate* – the bankruptcy defined at the sector-country-time level – is equal to 0.60 and highly statistically significant throughout the different model specifications. Quantitatively, a 10 p.p. increase in the sector default rate leads to a 6 p.p. increase in the likelihood that a firm in the same sector will file for bankruptcy in the subsequent year. The magnitude of the effect is fairly stable and robust to the inclusion of different sets of fixed effects that capture variation over time, as well as country and time differences. This indicates that industry distress and solvency conditions in each country are crucial to understand individual firm default. Moreover, the results are suggestive of a high risk that bankruptcy waves are triggered once insolvency starts to become material in a given sector. The addition of size category fixed effects in model 2 leaves the estimates qualitatively and quantitatively unchanged. Models 3-4 replicate the previous specifications including the variable *Distress* to the set of regressors. The coefficient estimate on this variable is positive and highly statistically significant. Quantitatively, companies that experience financial distress (i.e. negative equity) are by about 2 p.p. more likely to go bankrupt in the subsequent year, *ceteris paribus*. Hence, everything else equal, negative equity represents an important source of vulnerability, as it substantially increases the one-year ahead probability of default. The coefficient of *Sector Bankrate* is quantitatively unchanged and remains statistical significance, corroborating the view that aggregate sectoral shocks are important predictors of individual default.

Table 3: Determinants of default rates.

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
Negative ROA	0.0188***	0.0189***	0.0161***	0.0162***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ROA	-0.0148***	-0.0146***	-0.0153***	-0.0151***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LTA	0.0154***	0.0153***	0.0066***	0.0065***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial Expenses	0.1078***	0.1083***	0.1058***	0.1063***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Log(TA)	-0.0077***	-0.0079***	-0.0075***	-0.0077***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector Bankrate	0.6002***	0.6003***	0.5994***	0.5995***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Distress			0.0198***	0.0198***
			(0.0001)	(0.0001)
Observations	46,426,358	46,426,358	46,426,358	46,426,358
R-squared	0.0280	0.0280	0.0286	0.0286
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Size Cat. FE	No	Yes	No	Yes

The table reports estimation results of the bankruptcy model in equation 1. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Negative ROA* is a dummy variable equal to one if firm i's return on assets in year t is negative, and zero otherwise. *ROA* is the return on assets for firm i in year t. *LTA* is the ratio of total liabilities to total liabilities for firm i in year t. *Financialexpenses* is the ratio of financial expenses to total liabilities for firm i in year t. $Log(TA)$ is the logarithm of total assets firm i in year t. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. Models 1 and 3 include year, country and sector fixed effects, in models 2 and 4 we add size category fixed effects (indicators for micro, small, medium and large companies). Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Next, in Table 4 we replicate models 1-4 in Table 3 by considering insolvency that occurs among firms that are related through their activities along the supply chain. Specifically, we replace *Sector Bankrate* with the variable *Supply Chain disruption*, a variable that measures the bankruptcy rate along the entire supply chain of sector s in each country-year. Throughout the different model specifications, the coefficient of *Supply Chain disruption* is estimated positive and highly statistically significant. This result suggests that the overall health situation of the supply chain matters for corporate default. Thus, firm bankruptcy depends on the insolvency rate of the sectors to which a firm is linked in its operations. The size of the effect is non-negligible: a 10 p.p. increase in the default rate along the supply chain leads to a 6.5 p.p. increase in the likelihood that a firm will become insolvent in the following year. Finally, the coefficient on firm negative equity *Distress* is still positive and statistically significant, in line with the previous analysis in Table 3.

Table 4: Baseline including supply chain disruption.

	(1)	(2)	(3)	(4)
Dep. Var.	$Fail_{i,t+1}$			
Negative ROA	0.0175***	0.0176***	0.0148***	0.0149***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ROA	-0.0147***	-0.0145***	-0.0151***	-0.0148***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
LTA	0.0156***	0.0155***	0.0066***	0.0065***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial Expenses	0.0965***	0.0971***	0.0934***	0.0941***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Log(TA)	-0.0076***	-0.0079***	-0.0074***	-0.0078***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Supply chain disruption	0.6447***	0.6445***	0.6440***	0.6438***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Distress			0.0203***	0.0204***
			(0.0002)	(0.0002)
Observations	35,104,425	35,104,425	35,104,425	35,104,425
R-squared	0.0263	0.0264	0.0270	0.0270
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Size Cat. FE	No	Yes	No	Yes

The table reports estimation results of the bankruptcy model in equation 1. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year t+1, and zero otherwise. *NegativeROA* is a dummy variable equal to one if firm i's return on assets in year t is negative, and zero otherwise. *ROA* is the return on assets for firm i in year t. *LTA* is the ratio of total liabilities to total liabilities for firm i in year t. *Financial expenses* is the ratio of financial expenses to total liabilities for firm i in year t. $Log(TA)$ is the logarithm of total assets firm i in year t. *Supply Chain disruption* is the proportion of firms filing for bankruptcy in the supply chain of NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. Models 1 and 3 include year, country and sector fixed effects, in models 2 and 4 we add size category fixed effects (indicators for micro, small, medium and large companies). Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Motivated by the significant heterogeneity across size categories (see Section 2.1), Table 5 shows separate regressions for the sub-samples of micro (models 1 and 5), small (models 2 and 6), medium (models 3 and 7), and large (models 4 and 8) firms.

As a control for sectoral-level shocks, models 1-4 include the variable *Sector Bankrate*, while models 5-8 include, alternatively, the variable *Supply Chain disruption*. Estimates show that micro firms have higher probability of default when they make losses, have larger costs of debt, and are smaller. By contrast, for small, medium and large firms, size is no more a significant determinant of default, whereas profitability and leverage matter. Significant differences emerge across models for the coefficients of *Sector Bankrate*: for micro firms the value is equal 0.62, for small firms the value is roughly half (0.33), and less than half for the sub-samples of medium and large firms (0.24 and 0.27, respectively). The coefficients of *Supply Chain disruption* points to similar conclusions. This pattern suggests that micro firms are much more vulnerable to aggregate sectoral shocks. Otherwise said, their survival seems to be heavily affected by specific external economic conditions. Default of large firms is also affected by sector and supply chain shocks, but to a much smaller extent.

Table 5: Baseline including financial distress, by firm size category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				$Fail_{i,t+1}$				
	Micro	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**
Negative ROA	0.0161***	0.0132***	0.0109***	0.0063***	0.0149***	0.0120***	0.0102***	0.0059***
	(0.0001)	(0.0002)	(0.0004)	(0.0007)	(0.0001)	(0.0003)	(0.0005)	(0.0008)
ROA	-0.0147***	-0.0378***	-0.0280***	-0.0243***	-0.0146***	-0.0364***	-0.0267***	-0.0224***
	(0.0002)	(0.0011)	(0.0021)	(0.0040)	(0.0003)	(0.0012)	(0.0023)	(0.0044)
LTA	0.0053***	0.0267***	0.0198***	0.0048***	0.0052***	0.0267***	0.0203***	0.0055***
	(0.0001)	(0.0003)	(0.0006)	(0.0012)	(0.0001)	(0.0004)	(0.0007)	(0.0013)
Financial Expenses	0.0957***	0.1286***	0.0858***	0.0673***	0.0829***	0.1199***	0.0864***	0.0682***
	(0.0013)	(0.0033)	(0.0061)	(0.0102)	(0.0014)	(0.0039)	(0.0068)	(0.0111)
Log(TA)	-0.0082***	-0.0024***	-0.0028***	-0.0019**	-0.0082***	-0.0027***	-0.0028***	-0.0025***
	(0.0000)	(0.0001)	(0.0004)	(0.0008)	(0.0000)	(0.0001)	(0.0004)	(0.0009)
Sector Bankrate	0.6223***	0.3301***	0.2362***	0.2719***				
	(0.0021)	(0.0052)	(0.0089)	(0.0167)				
Distress	0.0196***	0.0297***	0.0210***	0.0198***	0.0201***	0.0296***	0.0208***	0.0191***
	(0.0001)	(0.0005)	(0.0009)	(0.0016)	(0.0002)	(0.0006)	(0.0010)	(0.0017)
Supply chain disruption					0.6673***	0.4141***	0.2987***	0.3325***
					(0.0029)	(0.0076)	(0.0124)	(0.0222)
Observations	39,909,808	4,987,248	1,214,786	314,516	30,217,197	3,645,910	972,608	268,710
R-squared	0.0298	0.0248	0.0186	0.0148	0.0282	0.0248	0.0190	0.0152
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model in equation 1 by firm size category. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Negative ROA* is a dummy variable equal to one if firm i's return on assets in year t is negative, and zero otherwise. *ROA* is the return on assets for firm i in year t. *LTA* is the ratio of total liabilities to total liabilities for firm i in year t. *Financial expenses* is the ratio of financial expenses to total liabilities for firm i in year t. $Log(TA)$ is the logarithm of total assets firm i in year t. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Supply Chaindisruption* is the proportion of firms filing for bankruptcy in the supply chain of NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. All specifications include year, country and sector fixed effects. Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

These findings are confirmed in Table 6 in which we interact the size category variable with *Sector Bankrate* (model 1) and *Distress* rate (model 2) to test for the statistical significance of the coefficients for the four different size classes of firms. We find that *Sector Bankrate* is a significantly larger predictor of default for micro companies. Additionally, the coefficient attached to financial distress is larger and significant for small and medium-sized companies when compared to the group of large firms.

Table 6: Determinants of default rates - Interaction with size category

	(1)	(2)	(3)
Dep. Var.		$Fail_{i,t+1}$	
Negative ROA	0.0162***	0.0159***	0.0149***
	(0.0001)	(0.0001)	(0.0001)
ROA	-0.0150***	-0.0156***	-0.0148***
	(0.0002)	(0.0002)	(0.0003)
LTA	0.0067***	0.0069***	0.0066***
	(0.0001)	(0.0001)	(0.0001)
Financial Expenses	0.1078***	0.1045***	0.0952***
	(0.0011)	(0.0011)	(0.0013)
Log(TA)	-0.0077***	-0.0078***	-0.0078***
	(0.0000)	(0.0000)	(0.0000)
Distress	0.0198***	0.0166***	0.0204***
	(0.0001)	(0.0015)	(0.0002)
Distress x Micro		0.0012	
		(0.0015)	
Distress x Small		0.0292***	
		(0.0016)	
Distress x Medium		0.0133***	
		(0.0018)	
Sector Bankrate	-0.0131	0.5988***	
	(0.0107)	(0.0019)	
Sector Bankrate x Micro	0.6774***		
	(0.0107)		
Sector Bankrate x Small	0.0952***		
	(0.0110)		
Sector Bankrate x Medium	-0.0193		
	(0.0119)		
Supply chain disruption			-0.1651***
			(0.0135)
Supply chain disruption x Micro			0.8838***
			(0.0135)
Supply chain disruption x Small			0.2114***
			(0.0140)
Supply chain disruption x Medium			-0.0040
			(0.0149)
Observations	46,426,358	46,426,358	35,104,425
R-squared	0.0292	0.0287	0.0276
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Size Cat. FE	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model in equation with interaction term with size category dummies. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Negatice ROA* is a dummy variable equal to one if firm i's return on assets in year t is negative, and zero otherwise. *ROA* is the return on assets for firm i in year t. *LTA* is the ratio of total liabilities to total liabilities for firm i in year t. *Financial expenses* is the ratio of financial expenses to total liabilities for firm i in year t. $Log(TA)$ is the logarithm of total assets firm i in year t. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Supply Chain disruption* is the proportion of firms filing for bankruptcy in the supply chain of NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. All specifications include year, country, sector fixed effects and size category fixed effects (indicators for micro, small, medium and large companies). Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration

3.2 Bankruptcy and the role of judicial efficiency

National bankruptcy regimes determine how orderly failing firms can exit the market or how speedily and efficiently those that are still viable can be restructured.[14] If well-designed, these institutional features play a crucial role in facilitating the reallocation of resources from ailing to more productive firms, thus ultimately maximising the potential productivity growth from firm exit. A few papers provide empirical evidence on the role of court efficiency, but limited to specific countries, often in the context of developing countries (Ponticelli and Alencar, 2016; Fonseca and Van Doornik, 2022). Nonetheless, the predictability and efficiency of national insolvency systems are even more important in a financially and economically integrated area like the European Union, where they represent key facilitating factors for cross-border investment and flows of market-based finance. Inefficiencies and major discrepancies in national insolvency laws act as substantive obstacles to the free movements of capital in the EU-27, in particular because diverging time-limits and lengths of procedures as well as diverging overall procedural efficiency make it more difficult to determine accurately the estimated recovery value, which may differ significantly from the actual recovery value, including for debt instruments. In fact, one of the flagship initiatives put forward by the European Commission under its Capital Markets Union Action Plan aims precisely at addressing these inefficiencies. In this perspective, our sample of firms operating in the EU-27 countries provides an interesting laboratory to investigate the role of judicial efficiency in the procedures for resolving insolvency as a determinant of corporate default.

In further tests, we formally examine how national bankruptcy regimes affect the probability of firms becoming insolvent. To do so, we complement our company data with information on the institutional framework for resolving financial distress

[14]Other institutional factors and country-specific characteristics have been identified as determinants of corporate default; among others, financial and economic crisis (Kim *et al.*, 2015; Carreira and Teixeira, 2016), credit supply (Fraisse *et al.*, 2018), bankruptcy law (Suarez and Sussman, 2007), local financial development (Fafchamps and Schu¨ ndeln, 2013), regional characteristics (Basile *et al.*, 2017), and other local conditions (Rozo, 2018).

and dealing with corporate insolvency drawn from the World Bank's Doing Business Project (for details see Djankov *et al.*, 2008). We focus on two specific features of national insolvency procedures, which in our view best proxy the inefficiency of the judicial system of a country in managing corporate bankruptcy. First, we consider the length of insolvency proceedings, defined as the time for creditors to recover their credit through reorganization, liquidation or debt enforcement (foreclosure or receivership) proceedings. Second, we examine the role of the recovery rate upon insolvencies, that is how many cents on the dollar claimants recover from an insolvent firm. For consistency among estimates, we build a measure of inefficiency as the unrecovered amount, calculated as one hundred minus the recovery rate (measured in percentage). We then augment the baseline estimation model with these two additional variables.

Results reported in Table 7 refer to judicial efficiency measured by the length of insolvency proceedings. Specifically, we replicate the baseline model with *Resolving insolvency* variable interacted with *Sector Bankrate* (model 1) or *Distress* (model 2 and 3) and *Supply Chain Disruption* (model 4). As the Resolving insolvency variables vary over countries and years, in all models we include country and year fixed effects, as well as industry and size category dummies. In discussing the estimates, we focus on the interaction term between our measure(s) of judicial (in)efficiency with the variables that capture firm-level distress and aggregate shocks, which are indicative of differential effects along the relevant dimensions. In column (1), we do not find a significant effect with the sectoral bankruptcy rate. By contrast, the estimates in column (4) suggest that there is a negative and significant interaction between supply chain disruptions and legal inefficiencies. Furthermore, the estimates in columns (2) and (3) show that when a firm is in distress, longer time of resolving insolvency decreases the probability of filing for bankruptcy in the following year. We interpret quantitatively these estimates with reference to estimates in column 2 of Table 7: the marginal effect of resolving insolvency, conditional on a firm being in financial distress ($Distress = 1$) is

-0.014 for countries where resolving insolvency takes one year, keeping other variables constant. The marginal effect is instead equal to -0.042 for countries where resolving insolvency takes three years. In words, reducing the time needed for resolving insolvency from three to one year increases the probability of bankruptcy of a distressed firm by about 3 percentage points.

Table 7: Resolving Insolvency - Time (years)

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
Distress	0.0199***	0.0507***	0.0482***	0.0204***
	(0.0001)	(0.0002)	(0.0003)	(0.0002)
Sector Bankrate	0.6013***	0.5926***		
	(0.0046)	(0.0019)		
Supply chain disruption			0.6396***	0.6926***
			(0.0027)	(0.0066)
Resolving insolvency (year)	0.0019***	0.0048***	0.0045***	0.0023***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Sector Bankrate x Resolving insolvency (year)	-0.0022			
	(0.0017)			
Distress x Resolving insolvency (year)		-0.0145***	-0.0134***	
		(0.0001)	(0.0001)	
Supply chain disruption x Resolving insolvency (year)				-0.0200***
				(0.0023)
Observations	46,413,552	46,413,552	35,096,424	35,096,424
R-squared	0.0286	0.0295	0.0277	0.0270
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Size Cat. FE	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model in equation with interaction terms with the variable *Resolving insolvency* (*year*). $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Negative ROA* is a dummy variable equal to one if firm i's return on assets in year t is negative, and zero otherwise. *ROA* is the return on assets for firm i in year t. *LTA* is the ratio of total liabilities to total liabilities for firm i in year t. *Financial expenses* is the ratio of financial expenses to total liabilities for firm i in year t. $Log(TA)$ is the logarithm of total assets firm i in year t. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Supply Chain disruption* is the proportion of firms filing for bankruptcy in the supply chain of NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. *Resolving insolvency* (*year*) is the time of insolvency proceedings to recover credit through reorganization, liquidation or debt enforcement (foreclosure or receivership) proceedings (source: Doing Business, the World Bank). All specifications include firm controls, year, country, industry and size category fixed effects. Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

In Table 8 we investigate the role of resolving insolvency by splitting the sample into the four size categories. Results suggest that the not significant interaction effect between *Sector Bankrate* and the length in resolving insolvencies in Table 7 is mostly driven by micro firms (model 1). Instead, small, medium and large firms display a negative and significant interaction coefficient (models 2-4). Distress and the length in resolving insolvencies is, by contrast, mostly driven by micro firms (model 5). The estimated coefficient on the interaction term is reduced in magnitude and significance when larger firms are considered (models 6 to 8).

Table 8: Resolving Insolvency - Time (years), by size category

Dep. Var.	(1)	(2)	(3)	(4) $Fail_{i,t+1}$	(5)	(6)	(7)	(8)
	Micro	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**
Sector Bankrate	0.6251***	0.5263***	0.3058***	0.3812***	0.6150***	0.3297***	0.2355***	0.2712***
	(0.0051)	(0.0122)	(0.0198)	(0.0375)	(0.0021)	(0.0052)	(0.0089)	(0.0167)
Distress	0.0196***	0.0297***	0.0211***	0.0198***	0.0500***	0.0421***	0.0273***	0.0192***
	(0.0001)	(0.0005)	(0.0009)	(0.0016)	(0.0002)	(0.0010)	(0.0018)	(0.0035)
Resolving insolvency (year)	0.0020***	0.0021***	0.0016***	0.0017***	0.0052***	0.0005***	0.0010***	0.0004
	(0.0001)	(0.0002)	(0.0003)	(0.0006)	(0.0001)	(0.0001)	(0.0003)	(0.0005)
Sector Bankrate x Resolving insolvency (year)	-0.0027	-0.0953***	-0.0384***	-0.0630***				
	(0.0018)	(0.0050)	(0.0092)	(0.0179)				
Distress x Resolving insolvency (year)					-0.0141***	-0.0063***	-0.0033***	0.0003
					(0.0001)	(0.0004)	(0.0008)	(0.0017)
	(0.0018)	(0.0050)	(0.0092)	(0.0179)				
Observations	39,901,314	4,984,170	1,213,793	314,275	39,901,314	4,984,170	1,213,793	314,275
R-squared	0.0298	0.0249	0.0187	0.0148	0.0306	0.0250	0.0187	0.0148
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model in equation with interaction terms with the variable *Resolving insolvency* (*year*) by considering separately firms belonging to different size category. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Negative ROA* is a dummy variable equal to one if firm i's return on assets in year t is negative, and zero otherwise. *ROA* is the return on assets for firm i in year t. *LTA* is the ratio of total liabilities to total liabilities for firm i in year t. *Financial expenses* is the ratio of financial expenses to total liabilities for firm i in year t. $Log(TA)$ is the logarithm of total assets firm i in year t. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Supply Chain disruption* is the proportion of firms filing for bankruptcy in the supply chain of NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. *Resolving insolvency* (*year*) is the time of insolvency proceedings to recover credit through reorganization, liquidation or debt enforcement (foreclosure or receivership) proceedings (source: Doing Business, the World Bank). All specifications include firm controls, year, country and sector fixed effects. Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Taken together, these findings suggest that legal inefficiencies occur in countries with larger levels of bankruptcy rates but, at the same time, generate a lag between the individual distress and the occurrence of liquidation. This implies that legal inefficiencies affect the business dynamics at macroeconomic level, eventually hampering a swift reallocation of investments towards more efficient firms. Our descriptive evidence corroborates this conjecture. More precisely, we separate EU-27 countries in two subgroups, a low and a high efficiency subgroup, which displays a value of the time of resolving insolvency above or below the median value, respectively. Then, in Table 9 we show that companies operating in countries with less efficient insolvency procedures are significantly smaller, more likely to experience distress, and less profitable, and hold more cash. Hence, overall, more inefficient judicial systems seem to be accompanied by a more vulnerable and financially fragile corporate sector.

Table 9: Summary statistics by Resolving Insolvency (time)

	Above median	**Below median**	**Diff.**
Fail	0.04	0.05	0.01□□□
Distress	0.31	0.14	-0.17□□□
ROA	-0.01	0.01	0.02□□□
Negative ROA	0.38	0.34	-0.04□□□
LTA	0.93	0.74	-0.19□□□
Financial expenses	0.02	0.02	0.00□□□
Log(TA)	11.08	12.62	1.53□□□
Number of employees	13.54	23.93	10.39□□□
Sector Bankrate	0.04	0.05	0.01□□□
Supply chain disruption	0.03	0.04	0.01□□□
Cash over TA	0.25	0.19	-0.06□□□
Age	15.20	18.80	3.60□□□
Observations	17978297	40437636	

Source: Own elaboration.

Finally, we replicate models in Tables 7 and 8 using the complement to the recovery rate upon insolvencies as a measure of judicial inefficiency at country-year level. Estimates in Tables 10 and 11 corroborate the evidence discussed above on the role of judicial inefficiency in determining bankruptcy probabilities of companies when facing sector shocks or individual financial distress.

Table 10: Resolving Insolvency - Recovery rate

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
Distress	0.0199***	0.0420***	0.0389***	0.0204***
	(0.0001)	(0.0002)	(0.0003)	(0.0002)
Sector Bankrate	0.6618***	0.6042***		
	(0.0047)	(0.0020)		
Supply chain disruption			0.6543***	0.8329***
			(0.0027)	(0.0068)
Resolving insolvency (100-rate)	0.0004***	0.0004***	0.0004***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector Bankrate x Resolving insolvency (100-rate)	-0.0010***			
	(0.0001)			
Distress x Resolving insolvency (100-rate)		-0.0005***	-0.0005***	
		(0.0000)	(0.0000)	
Supply chain disruption x Resolving insolvency (100-rate)				-0.0032***
				(0.0001)
Observations	46,413,552	46,413,552	35,096,424	35,096,424
R-squared	0.0287	0.0291	0.0274	0.0271
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Size Cat. FE	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model in equation with interaction terms with the variable *Resolving Insolvency*$(100 - rate)$. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Supply Chain disruption* is the proportion of firms filing for bankruptcy in the supply chain of NACE industry s, country c and in year t. *Resolving Insolvency*$(100 - rate)$ is the one hundred minus the recovery rate upon insolvencies, that is how many cents on the dollar claimants recover from an insolvent firm (source: Doing Business, the World Bank). All specifications include firm controls, year, country, industry and size category fixed effects. Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Table 11: Resolving Insolvency - Recovery rate, by size category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				$Fail_{i,t+1}$				
	Micro	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**
Sector Bankrate	0.6830***	0.5911***	0.3112***	0.3471***	0.6270***	0.3294***	0.2362***	0.2648***
	(0.0053)	(0.0118)	(0.0169)	(0.0313)	(0.0021)	(0.0053)	(0.0090)	(0.0169)
Distress	0.0197***	0.0296***	0.0211***	0.0198***	0.0413***	0.0364***	0.0284***	0.0298***
	(0.0001)	(0.0005)	(0.0009)	(0.0016)	(0.0002)	(0.0011)	(0.0019)	(0.0033)
Resolving insolvency (100-rate)	0.0004***	0.0003***	0.0001***	0.0000	0.0004***	0.0000	0.0000	-0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector Bankrate x Resolving insolvency (100-rate)	-0.0010***	-0.0059***	-0.0020***	-0.0023***				
	(0.0001)	(0.0002)	(0.0004)	(0.0007)				
Distress x Resolving insolvency (100-rate)					-0.0005***	-0.0002***	-0.0002***	-0.0003***
					(0.0000)	(0.0000)	(0.0000)	(0.0001)
Observations	39,901,314	4,984,170	1,213,793	314,275	39,901,314	4,984,170	1,213,793	314,275
R-squared	0.0299	0.0250	0.0187	0.0149	0.0303	0.0249	0.0187	0.0149
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model in equation with interaction terms with the variable *Resolving Insolvency*$(100 - rate)$ by considering separately firms belonging to different size category. $Fail_{i,t+1}$ is a dummy variable equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise. *Sector Bankrate* is the proportion of firms filing for bankruptcy in NACE industry s, country c and in year t. *Distress* is a dummy variable equal to one if firm i reports negative values of shareholder funds in year t, and zero otherwise. *Resolving Insolvency*$(100 - rate)$ is the one hundred minus the recovery rate upon insolvencies, that is how many cents on the dollar claimants recover from an insolvent firm (source: Doing Business, the World Bank). All specifications include firm controls, year, country and sector fixed effects. Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

3.3 Robustness

In this section, we provide several robustness checks to our main findings. First, we estimate the baseline model adding other potential determinants of bankruptcy, notably a measure of firm liquidity (*Cash over TA*), defined as cash and cash equivalent over total assets, and an indicator for firm age (*Age*). We use these controls because firms benefit from holding cash (Opler *et al.*, 1999), which in turn affects growth opportunities, asset liquidation, and financial distress, especially among smaller firms (Martínez-Sola *et al.*, 2018). Also, early empirical studies have highlighted the role of firm age in broad firm dynamics (Haltiwanger *et al.*, 2013). For conciseness, in Table A1 we report only the estimates by size category. We find that the cash ratio does seem to play a not significant role for micro firms and a positive role in explaining bankruptcy for the others. By contrast, *Age* is negative and statistically significant especially for the micro firms sub-sample. This is in line with works documenting that micro firms are particularly vulnerable in the early stages of their life-cycle (see, e.g., Wagner, 1994; Mueller and Stegmaier, 2015). Importantly, our main coefficients of interest are substantially unchanged after the inclusion of these controls. We further explore the role of *Age* among micro firms in Table A2 to study whether our conclusions differ between young firms (business start-ups) and relatively more mature ones. When we split the sample based on the average age, we find similar results in the two subgroups. A remarkable difference is that *Distress* is a stronger predictor of bankruptcy among mature firms, while for younger firms negative equity does not necessarily lead to insolvency.

An additional concern is whether our evidence on *Sector Bankrate* is driven by the underlying macroeconomic conditions, as highlighted in Altman (1983), and other country-specific time-varying characteristics. Table A3 reports the estimates after controlling for year×country fixed effects, in addition to sector fixed effects.[15] Results confirm the informativeness of *Sector Bankrate* in predicting bankruptcy as well as mi-

[15]Estimates with macro controls are available upon request.

cro firms' marked vulnerabilities to sectoral shocks.[16]

Additionally, we estimate our model using a non-linear functional form. Table A4 presents the baseline results using a logistic regression. Panel A reports the coefficients confirming the importance of firms characteristics in predicting bankruptcy. The marginal effects in panel B show that an additional increase in the *Sector Bankrate* increases the probability of bankruptcy by 51 percentage points.[17] Similarly, by replicating the logit model by size category, marginal effects confirm the differential impacts of firm variables and *Sector Bankrate* (Panel C). For example, an additional increase in the *Sector Bankrate* raises the probability of bankruptcy by 39 percentage points for micro firms but 15 percentage points for medium and large firms.

Finally, we run the baseline model by adding imputed variables for missing values among independent variables.[18] The rationale for this analysis is to check for the robustness of our estimates by including excluded firms due to missing observations, a concern that is especially relevant for smaller and more opaque firms. After the imputation, the sample size increases substantially. Estimates in Table A5 are quantitatively in line with baseline estimates, suggesting that missing values do not generate significant bias in our main sample.

4 Conclusions

In this paper, we study the determinants of corporate bankruptcy using a large sample of companies from the EU-27 in the period 2007-2018. Our analysis examines the differences in the probability of bankruptcy across firm size categories (micro, SMEs and large firms) and highlights the role of institutional heterogeneity regarding the efficiency of insolvency procedures. Our findings indicate that default probability of

[16]Results for Supply chain disruption in a model that includes country per year fixed effects are in line with those obtained in Table 4 and are available upon request.

[17]Marginal effects represent the change in the probability for an infinitesimal change in each independent, continuous variable, and the discrete change in the probability of dummy variables.

[18]We use the impute routine in Stata where the independent variables are the ones employed in the baseline model.

micro and small firms is significantly affected by financial distress and by the efficiency of the host country judicial system. Smaller firms are significantly more vulnerable to sectoral shocks and to disruptions along their supply chain. Furthermore, companies in financial distress are more likely to default. These impacts are larger in jurisdictions that display a relatively faster process in resolving insolvencies - a stylized fact mostly driven by smaller companies. Taken together, our findings indicate that the efficient resolution of insolvency may ultimately enables the orderly liquidation of non-viable firms in the short-run. We leverage on our results to derive some policy implications. In particular, the harmonisation of national insolvency regimes in the EU-27 towards most efficient legal practices, as foreseen under the Capital Markets Union Action Plan, may imply larger number of defaults in the short-run, following deteriorated corporate financial conditions in the wake of the recent economic crises, like the Covid-19. At the same time, faster and more efficient resource reallocation from distressed firms to more productive ones may imply a long-run decrease in bankruptcy rates, and a potential reduction in the number of distressed or ’zombie’ firms, a phenomenon that has been on the rise in the last decades, even before the recent pandemic crisis.

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List of Figures

List of Tables

Annex - Additional Tables

Table A1: Robustness I: controlling for additional firm determinants

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
	Micro	**Small**	**Medium**	**Large**
Negative ROA	0.0137***	0.0124***	0.0107***	0.0053***
	(0.0001)	(0.0003)	(0.0004)	(0.0008)
ROA	-0.0149***	-0.0403***	-0.0284***	-0.0277***
	(0.0003)	(0.0012)	(0.0022)	(0.0042)
LTA	0.0033***	0.0254***	0.0200***	0.0061***
	(0.0001)	(0.0004)	(0.0007)	(0.0013)
Financial Expenses	0.0892***	0.1265***	0.0828***	0.0580***
	(0.0013)	(0.0037)	(0.0062)	(0.0103)
Log(TA)	-0.0060***	-0.0016***	-0.0012***	0.0005
	(0.0000)	(0.0001)	(0.0004)	(0.0009)
Sector Bankrate	0.5961***	0.3069***	0.2165***	0.2403***
	(0.0023)	(0.0058)	(0.0092)	(0.0167)
Distress	0.0175***	0.0279***	0.0198***	0.0185***
	(0.0002)	(0.0006)	(0.0010)	(0.0018)
Cash over TA	0.0001	0.0015***	0.0034***	0.0113***
	(0.0002)	(0.0005)	(0.0011)	(0.0027)
Age	-0.0005***	-0.0001***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	30,975,279	3,790,537	1,103,142	281,718
R-squared	0.0255	0.0234	0.0179	0.0137
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model run separately for each size category. Additional determinants included are *Cash over TA*, the ratio of cash and cash equivalent to total assets for firm i in year t, and *Age*, the difference between year t and the incorporation year for firm i in year t. All specifications include year, country and sector fixed effects. Size categories are defined according to the definition by the European Commission. t-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Table A2: Robustness II: the role of Age among micro firms

	(1)	(2)
Dep. Var.	$Fail_{i,t+1}$	
	Young	**Mature**
Negative ROA	0.0125***	0.0159***
	(0.0002)	(0.0001)
ROA	-0.0077***	-0.0212***
	(0.0005)	(0.0003)
LTA	0.0035***	0.0050***
	(0.0002)	(0.0001)
Financial Expenses	0.0704***	0.1004***
	(0.0029)	(0.0014)
Log(TA)	-0.0050***	-0.0090***
	(0.0000)	(0.0000)
Sector Bankrate	0.6285***	0.5934***
	(0.0077)	(0.0022)
Distress	0.0147***	0.0213***
	(0.0003)	(0.0002)
Observations	7,730,642	32,179,166
R-squared	0.0337	0.0300
Year FE	Yes	Yes
Country FE	Yes	Yes
Sector FE	Yes	Yes

The table reports estimation results of the bankruptcy model run separately for two sub-samples of micro firms: model 1 includes young firms (Age lower or equal 10), model 2 includes mature firms (Age above 10). All specifications include year, country and sector fixed effects. *t*-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Table A3: Robustness III: controlling for macroeconomic time-varying effects

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
	Micro	**Small**	**Medium**	**Large**
Negative ROA	0.0162***	0.0132***	0.0109***	0.0062***
	(0.0001)	(0.0002)	(0.0004)	(0.0007)
ROA	-0.0153***	-0.0379***	-0.0279***	-0.0242***
	(0.0002)	(0.0011)	(0.0021)	(0.0040)
LTA	0.0051***	0.0264***	0.0196***	0.0049***
	(0.0001)	(0.0003)	(0.0006)	(0.0012)
Financial Expenses	0.0951***	0.1314***	0.0911***	0.0679***
	(0.0013)	(0.0033)	(0.0061)	(0.0102)
Log(TA)	-0.0082***	-0.0025***	-0.0030***	-0.0019**
	(0.0000)	(0.0001)	(0.0004)	(0.0008)
Sector Bankrate	0.7071***	0.3896***	0.2227***	0.2780***
	(0.0050)	(0.0118)	(0.0162)	(0.0280)
Distress	0.0199***	0.0295***	0.0209***	0.0199***
	(0.0001)	(0.0005)	(0.0009)	(0.0016)
Observations	39,909,804	4,987,248	1,214,786	314,516
R-squared	0.0327	0.0270	0.0214	0.0178
Year * Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model run separately for each size category. All models include year×country and sector fixed effects. Size categories are defined according to the definition by the European Commission. *t*-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Table A4: Robustness IV: logit model

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
Panel A				
Negative ROA	0.5732***	0.5719***	0.5130***	0.5121***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
ROA	-0.0546***	-0.0655***	-0.0606***	-0.0700***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
LTA	0.3502***	0.3522***	0.1671***	0.1696***
	(0.0015)	(0.0015)	(0.0020)	(0.0020)
Financial Expenses	2.6901***	2.7067***	2.6130***	2.6300***
	(0.0342)	(0.0343)	(0.0341)	(0.0342)
Log(TA)	-0.2070***	-0.1998***	-0.2043***	-0.1981***
	(0.0005)	(0.0006)	(0.0005)	(0.0006)
Sector Bankrate	14.7326***	14.7198***	14.6652***	14.6533***
	(0.0448)	(0.0448)	(0.0448)	(0.0448)
Distress			0.4015***	0.3997***
			(0.0029)	(0.0029)
Panel B				
Negative ROA	0.0235***	0.0235***	0.0192***	0.0191***
	(0.0028)	(0.0028)	(0.0024)	(0.0025)
ROA	0.0019	0.0017	0.0023	0.0021
	(0.0017)	(0.0016)	(0.0016)	(0.0014)
LTA	0.0036***	0.0037***	0.0012	0.0012
	(0.0011)	(0.0011)	(0.0009)	(0.0008)
Financial Expenses	0.0549***	0.0556***	0.0628***	0.0635***
	(0.0160)	(0.0160)	(0.0174)	(0.0174)
Log(TA)	-0.0069***	-0.0066***	-0.0067***	-0.0065***
	(0.0010)	(0.0009)	(0.0010)	(0.0010)
Sector Bankrate	0.5133***	0.5130***	0.5091***	0.5089***
	(0.0836)	(0.0835)	(0.0817)	(0.0816)
Distress			0.0188***	0.0187***
			(0.0035)	(0.0036)
Observations	46,426,354	46,426,354	46,426,354	46,426,354
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Size Cat. FE	No	Yes	No	Yes
Panel C				
	Micro	**Small**	**Medium**	**Large**
Negative ROA	0.0129***	0.0110***	0.0092***	0.0055***
	(0.0001)	(0.0001)	(0.0002)	(0.0004)
ROA	-0.0024***	-0.0082***	-0.0064***	-0.0094***
	(0.0001)	(0.0004)	(0.0009)	(0.0018)
LTA	0.0038***	0.0128***	0.0096***	0.0022***
	(0.0001)	(0.0002)	(0.0003)	(0.0006)
Financial Expenses	0.0578***	0.0791***	0.0503***	0.0403***
	(0.0010)	(0.0022)	(0.0038)	(0.0066)
Log(TA)	-0.0056***	-0.0005***	-0.0002	-0.0003
	(0.0000)	(0.0001)	(0.0001)	(0.0003)
Sector Bankrate	0.3932***	0.2078***	0.1470***	0.1482***
	(0.0013)	(0.0031)	(0.0052)	(0.0092)
Distress	0.0106***	0.0066***	0.0045***	0.0062***
	(0.0001)	(0.0002)	(0.0003)	(0.0006)
Observations	39,909,804	4,987,248	1,214,786	314,516
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes

The table reports estimation results of the bankruptcy model using logistic regression. Panels A and B show the estimated coefficients and the marginal effects, respectively. Models 1 and 3 include year, country and sector fixed effects, in models 2 and 4 we add size category fixed effects (indicators for micro, small, medium and large companies). Panel C reports the marginal effects after running separate logit model for each size category. Size categories are defined according to the definition by the European Commission. *t*-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

Table A5: Determinants of default rates (imputing missing data)

	(1)	(2)	(3)	(4)
Dep. Var.		$Fail_{i,t+1}$		
Negative ROA	0.0184***	0.0184***	0.0158***	0.0159***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ROA	-0.0137***	-0.0136***	-0.0142***	-0.0140***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LTA	0.0141***	0.0140***	0.0056***	0.0056***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial Expenses	0.0919***	0.0923***	0.0901***	0.0905***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Log(TA)	-0.0076***	-0.0077***	-0.0073***	-0.0075***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector Bankrate	0.5611***	0.5611***	0.5605***	0.5606***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Distress			0.0195***	0.0195***
			(0.0001)	(0.0001)
Observations	52,768,765	52,768,765	52,768,765	52,768,765
R-squared	0.0266	0.0266	0.0272	0.0272
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Size Cat. FE	No	Yes	No	Yes

The table reports estimation results of the bankruptcy model in equation 1 after imputing missing data. Models 1 and 3 include year, country and sector fixed effects, in models 2 and 4 we add size category fixed effects (indicators for micro, small, medium and large companies). Size categories are defined according to the definition by the European Commission. *t*-statistics based on robust standard errors and are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. Source: Own elaboration.

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