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Firms in Financial Distress

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Abstract We use simple accounting measures to estimate the share of private manufacturing firms in financial distress under a hypothetical scenario of losing half their sales from the previous year. We study the characteristics of these financially distressed firms and find that, consistent with Schumpeter's theory, young, small, domestic market oriented and single-product firms are more likely to fall into financial distress, particularly in Western Africa.

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1. Introduction

Past financial crises have raised important questions about the proper role of government in preventing and alleviating the financial distress of private business (Djankov and Panizza 2020). Government actions to assist companies or sectors of the economy raise equity issues, as governments resort to taxing other companies to service the additional public debt resulting from this assistance. Government involvement also raises the concern that private businesses come to expect such assistance and may behave in imprudent ways, leading to future crises (Claessens, Djankov and Mody 2001).

Economists associate the mass distress of firms during recessions with Schumpeter (1934)'s creative destruction theory, where during downturns small, less efficient, younger firms are the ones to exit the market. Their exit allows for more efficient firms to expand and prosper, lifting overall productivity.

In this paper we use simple accounting measures to estimate the share of private manufacturing firms under financial distress across 34 countries and 6 sectors. We use a scenario of sales falling to half of their previous year's value to calculate the share of firms in financial distress. We study the characteristics of these financially-distressed firms and find that, consistent with Schumpeter's theory, young, small, domestic market oriented and single-product firms are more likely to fall into financial distress, particularly in Western Africa.

Section 2 describes the data. Section 3 surveys the literature on financial distress. Section 4 describes the methodology, estimates insolvency risk with a simple scenario of sales reaching only half of their last year's value and looks at the characteristics of financially distressed firms. Section 5 examines corporate distress in 16 African economies and finds that Schumpeter's predictions ring true in particular for Western African firms. Section 6 concludes.

2. Data

We use firm-level data for over 11,148 firms across 34 countries to approximate the financial distress of manufacturing companies. We rely on firms' responses to various questions in the World Bank's Enterprise Surveys regarding firms' age, sales, costs, external financing, employment, export orientation and product diversification.

Each firm is coded with one of the International Standard Industrial Classification (ISIC) codes, which we group into 6 broader manufacturing industries. These are Chemical Manufacturing (ISIC 3.1 Rev 19-21); Electronics & Equipment Manufacturing (26-30); Leather, Wood & Paper Manufacturing (15-17); Metal Manufacturing (24-25); Nonmetal Manufacturing (22-23); and Other Manufacturing (18, 31-34). Tables 1 and 2 give details on the sample by sector and by country.

Table 1: Manufacturing Industry Sample

Sector	Sample Size	Firms with Full Income Data	Exporters
Chemical Manufacturing	680	457	229
Electronics and Equipment Manufacturing	3441	1960	1093
Leather, Wood, and Paper Manufacturing	3443	2200	1079
Metal Manufacturing	1185	738	452
Nonmetal Manufacturing	418	244	77
Other Manufacturing	1981	1109	815

Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

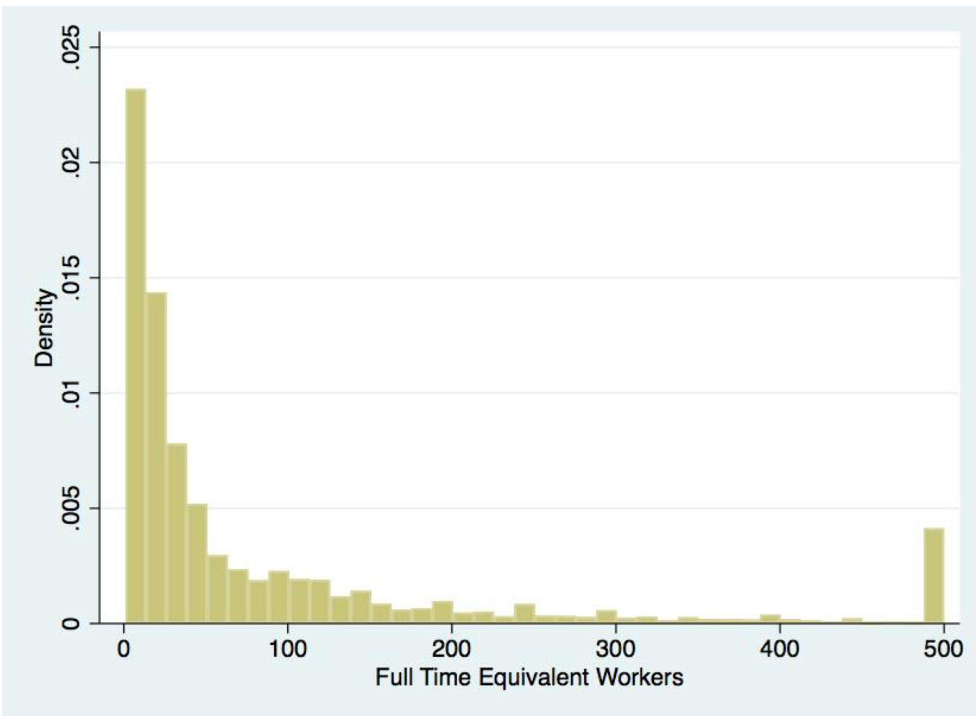
Table 2: Country Sample

Country	Survey Year	Sample Size	Firms with Full Income Data	Exporters
Benin	2016	59	49	17
Bolivia	2017	109	49	27
Cambodia	2016	126	120	36
Cameroon	2016	69	32	22
Colombia	2017	547	311	182
Côte d'Ivoire	2016	87	49	32
Egypt	2016	1113	862	310
El Salvador	2016	336	207	141
Gambia	2018	57	55	8
Greece	2018	299	281	196
Honduras	2016	78	49	26
Italy	2019	436	316	225
Jordan	2019	274	59	129
Kazakhstan	2019	843	312	94
Kenya	2018	408	290	198
Kyrgyz Republic	2019	143	58	49
Liberia	2017	63	53	7
Mali	2016	73	37	29
Moldova	2019	124	90	74
Mongolia	2019	120	98	25
Morocco	2019	312	91	125
Mozambique	2018	247	213	55
Myanmar	2016	331	300	40
Nicaragua	2016	98	83	31
Portugal	2019	730	378	374
Russia	2019	789	385	188
Rwanda	2019	100	98	39
Sierra Leone	2017	59	48	8
Turkey	2019	960	499	389
Ukraine	2019	882	369	349
Uzbekistan	2019	747	447	178
West Bank/Gaza	2019	108	72	38
Zambia	2019	158	126	42
Zimbabwe	2016	263	222	62
Totals		11148	6708	3745

Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

We examine several firm characteristics that the previous literature relates to the likelihood to succumb to financial distress. The first proxy for firm size is the number of "full time equivalent workers" (employees) in the previous fiscal year. This number is calculated adding the number of full-time permanent workers and the adjusted employment of temporary workers using the average duration of a temporary contract for each firm. For the sample population of 11,148 firms, the employees' mean is 123 while the median is 30 (figure 1).

Figure 1: Density of Firms' Employment



Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

Looking at variations by country, Gambia had the lowest average employee count with 18 workers, while Cambodia had the highest with 355. For median workers, Gambia again had the lowest with 9 workers while Morocco had the highest with 56 workers. By sector, Nonmetals had the lowest average employment at 57, while Other Manufacturing had the highest with 155. The Nonmetals sector has the lowest median number, with 18 employees, while Metal Manufacturing had the highest median, with 36.

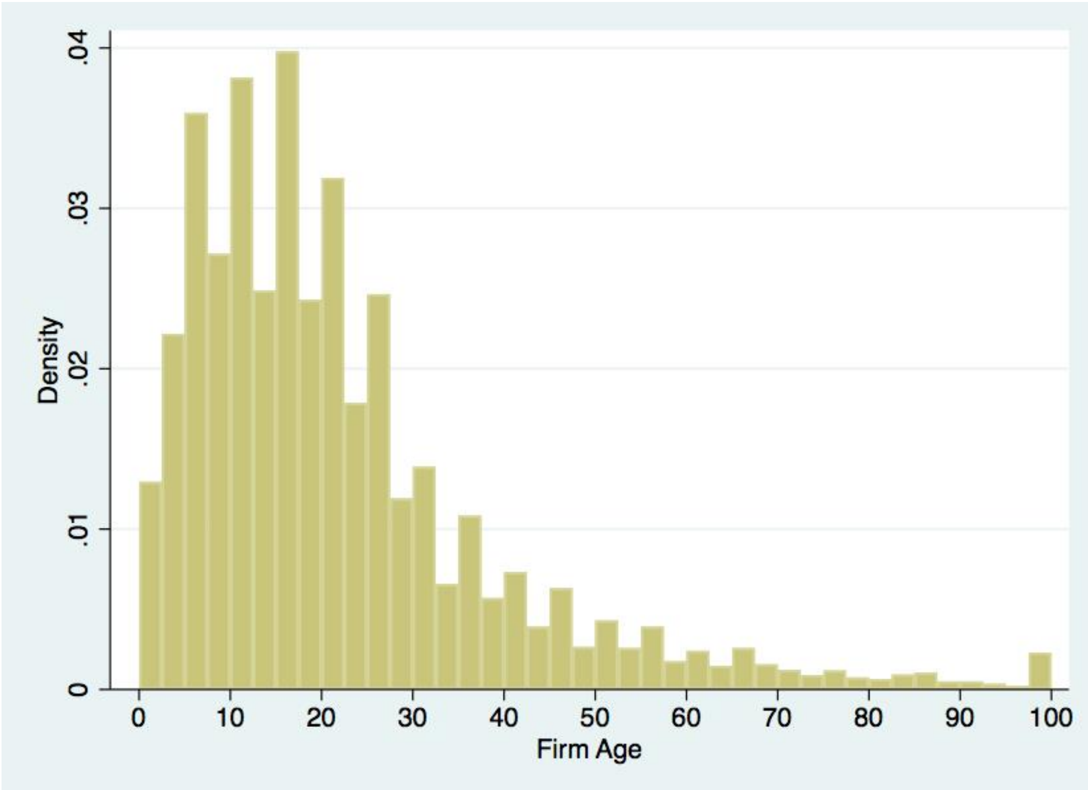
The second proxy for firm size is a firm's total sales from the previous fiscal year, expressed in local currency. Country fixed-effects allow for the data to be used in cross-sectional regressions without converting to a uniform currency.

Our third variable of interest is firm age. Within the 11,148 sample observations, firms have ages clustered between 0 and 50 years, with 99% of the companies being younger than 100 years old. The average firm age is 22 years, while the median is 17 years. By country, Uzbekistan had the lowest average firm age of 12 years, while Italy had the highest average of 35 years. For median age, Rwanda and Uzbekistan have the lowest age of 9 years while Italy again had the highest of 31 years (figure 2).

By sector, Other Manufacturing has the lowest average firm age of 19 years while Chemical Manufacturing has the highest of 23 years. For median firm age, Other Manufacturing has the lowest of 16 years while Chemical Manufacturing has the highest of 19 years.

In addition to the main variables relating to firm size and age, we use two control variables to account for different aspects of firm exposure to crises: product/service diversification and reliance on exports for sales revenue. We proxy firm diversification based on survey responses to the question "In the last Fiscal Year, what percent of your total annual sales came from your main product/service?". We find that the majority of firms have low levels of diversification. The sample mean for the percent of annual sales from the main business function is 88% while the median is 100%.

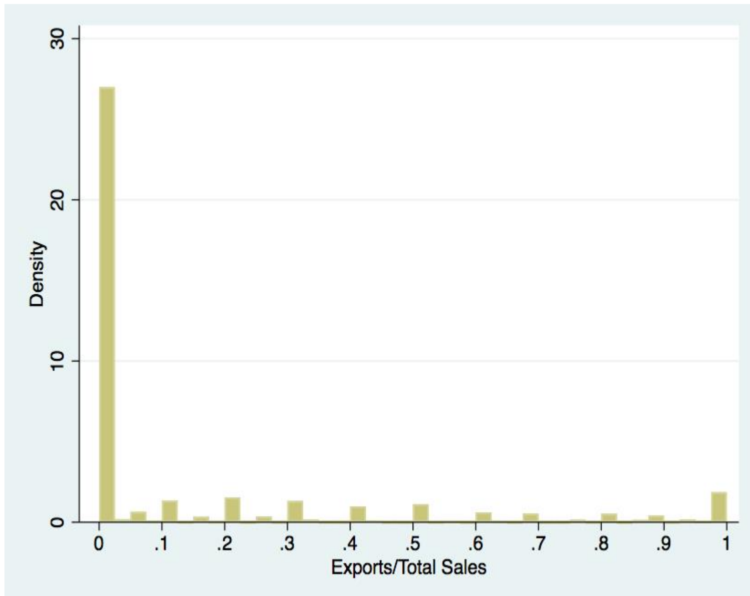
Figure 2: Density of Firm Age



Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

For export intensity, we use firms' responses to the question "In the last Fiscal Year, what percent of your total annual sales came from direct as well as indirect exports?". Looking at the distribution of export reliance, we see that many firms do not export at all: 50% of firms reported no exporting and the mean fraction of sales from exports is merely 15% percent. By country, Sierra Leone had the lowest average export reliance of 3% while Moldova had the highest average of 39%. By sector, Nonmetals had the lowest average of 6% while Other Manufacturing had the highest average of 25%.

Figure 3: Density of Firms' Export Reliance



Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

3. Literature Review

There exists a large literature on predicting corporate distress, varying by the choice of accounting or market data as well as the methodology used to forecast the likelihood and time horizon of insolvency. Beaver (1966) is the first to examine the usefulness of standard financial accounting ratios in predicting firm failure. Altman (1968) develops a widely used Z-Score for publicly traded manufacturing firms using both accounting and market data. Ohlson (1980) develops an O-score as an alternative, also using static accounting ratios for predicting insolvency. Zmijewski (1984) examines the methodological issues in the development of such prediction models based on their respective sample selection biases.

Using accounting ratios to predict bankruptcy has had a wide range of applications. Dichev (1998), for example, uses ratio predictions to show that firm bankruptcy risk is not rewarded with higher returns but rather anomalously lower returns. Griffin and Lemmon (2002) used the O-Score to examine the relationship between book-to-market equity, distress risk and stock returns, showing that firms with high distress risk exhibit large return reversals around earnings announcement. Ferguson and Shockley (2003) also use static ratios to explore risk and average returns in the CAPM and Fama-French three factor models for publicly traded stocks.

Accounting ratios have alternatively been used to predict credit ratings, which are subjectively dependent on default probabilities provided by credit rating agencies. Kaplan and Urwitz (1979) use a linear model of accounting and market measures to predict bond ratings, often assessing the actual risk of a bond more accurately than the rating agency itself. Blume, Lim, and MacKinlay (1998) use predictive ratios to show that bond rating standards became more stringent between 1978 and 1995, demonstrating that the overall downward trend in corporate bond ratings over the same period was not due solely to a deterioration in the credit quality of U.S. corporate debt. Molina (2005) also employs ratios to show that firms are not underleveraged as the increased costs of financial distress often offset the estimates of the tax benefits of debt. Avramov et al. (2007) explore the relationship between market momentum, stock returns, liquidity and credit ratings.

Subsequent research has made significant improvements on the static ratio prediction analyses based on the O and Z-scores. Shumway (2001) estimates a dynamic hazard model using time-varying accounting and market measures, showing the benefits to accuracy of eliminating biases and overestimates that can arise from using static predictions. Chava and Jarrow (2004) expand on Shumway's dynamic hazard model by using monthly data, as well as demonstrate the importance of industry effects in predicting bankruptcy. Beaver, McNichols, and Rhie (2005) examine the effect of changes in financial reporting standards on bankruptcy prediction coefficients, showing the robustness of the hazard model to predict bankruptcies over a fortyyear period. Duffie, Saita, and Wang (2007) emphasize the importance of considering time horizons when predicting firm failure using time varying firm-specific and macroeconomic covariates. They find that the term structure of conditional future default probabilities depends on a firm's distance to default, its trailing stock return, general trailing market returns, and the prevailing interest rates.

The recent literature has continued to refine the predictive power of bankruptcy forecasting. Campbell, Hilscher, and Szilagyi (2008) employ a dynamic logit model with accounting and market variables to explore the determinants of corporate failures and the pricing of financially distressed stocks whose failure probability is high. Their findings contradict the common hypothesis that value and size effects are compensation to stockholders for the risk of financial distress, as financially distressed stocks deliver lower returns with higher standard deviations, market betas, and loadings on value and small-cap risk factors.

Bharath and Shumway (2008) examine the accuracy of the Merton (1974) bond pricing model which calculates distance to default. They find that an expanded hazard model outperforms the Merton model for predicting default probabilities, and implied default probabilities from credit default swaps and corporate bond yield spreads are only weakly correlated with the Merton probabilities. While they conclude that the Merton model does not produce sufficient statistics for the probability of default, its functional form is still useful for forecasting defaults. Agarwal and Taffler (2008) compare the effectiveness of recently developed prediction models that use a contingent claims valuation approach with the traditional Altman z-score. They find that the two approaches capture different aspects of bankruptcy risk, but the z-score leads to significantly greater bank profitability in conditions of differential decision error costs and competitive pricing regime.

Tinoco and Wilson (2013) demonstrate the efficacy of combining accounting, market-based and macro-economic data to predict financial distress for publicly listed companies. Their results compare favorably with established models that utilize neural networks as well as Altman's (1968) original z-score. Azizpour, Giesecke, and Schwenkler (2018) study the sources of corporate default clustering in the United States. They find strong evidence that contagion between firms is a significant clustering source with important implications for pricing and managing correlated default risk.

In sum, the literature predicting corporate distress has evolved substantially over the past half century. Still, the Altman z-score model is used widely on account for its parsimony with accounting data. This is particularly the case for privately-held companies, where market data are not available.

4. Simulating Corporate Distress

We employ Altman's (1983) version of the Z-score, as adapted for private firms. The private specification of the Z-score is an alternative to the original 1968 score that allows for the substitution of book value of equity instead of market value of equity, data available from the World Bank's Enterprise Survey. The Altman Z-Score employs seven accounting ratios: earnings before income and taxes (EBIT), total assets, net sales, the book value of equity, total liabilities, working capital, and retained earnings. It is calculated as follows:

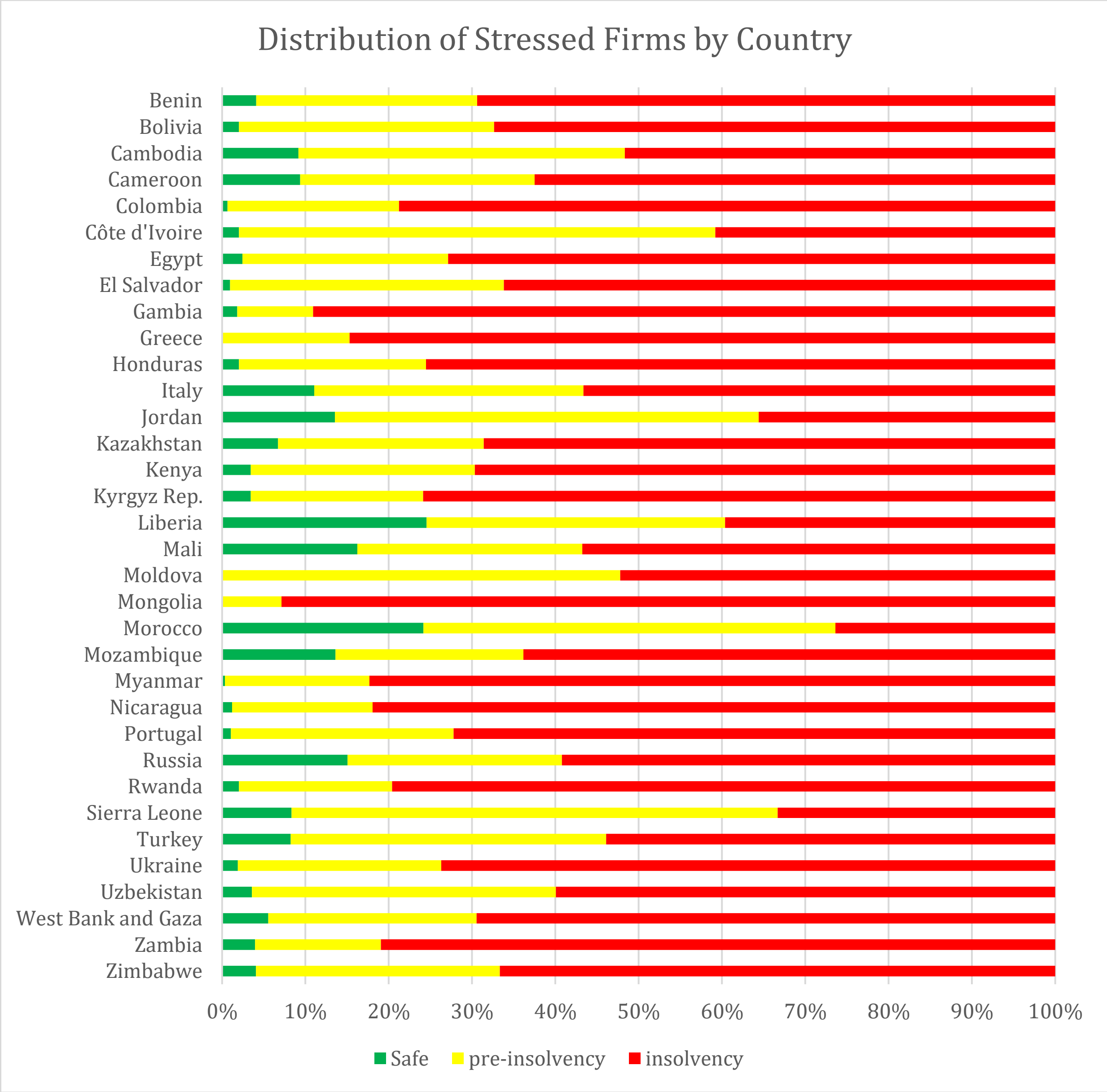
Altman Z-Score (Private Firms) = ((EBIT/Total Assets) x 3.107) + ((Net Sales/Total Assets) x 0.998) + ((Book Value of Equity/Total Liabilities) x 0.420) + ((Working Capital/Total Assets) x 0.717) + ((Retained Earnings/Total Assets) x 0.847)

A score above 2.9 is indicative of a solvent firm. A score between 1.23 and 2.9 relates to firms that should be on alert for insolvency risk. A score below 1.23 is highly predictive of insolvency. Since we do not have access to standard balance sheets in the data, we make assumptions based on survey responses to obtain the needed ratio inputs. EBIT is calculated as the firm's total annual sales minus its total costs of goods sold. Total Assets is approximated as the sum of total sales and the market value of the firm's machinery. Net Sales uses the annual sales responses. Working Capital and Retained Earnings are both approximated as the firm's profit after taxes, the latter also assuming 10% dividends and 15% depreciation. To calculate the firm's total debt, we utilize responses to the question "What percent of your working capital is financed from internal funds/retained earnings?". Book Value of Equity is the difference between total assets and outstanding debt, and total liabilities is the sum of Equity and Debt.

To establish a baseline of distress indicators, we examine the mean and median z-score of each industry, as well as the distribution of solvent, at risk, and insolvent firms according to Altman (1983). Electronics and Equipment Manufacturing and Other Manufacturing firms both had the highest average z-score of 1.9 while Chemical Manufacturing had the lowest score of 1.78. For median scores, Other Manufacturing had the highest score of 1.67 while Metal Manufacturing had the lowest score of 1.57.

We first observe that for all industries the majority of firms fall under the "grey area" of at risk. To make comparisons across sectors of different sizes, we display the same distribution as a fraction of the total firms in each sector. Every sector had at least 20% of its firms fall under the "at risk" category.

Figure 4: Simulated Insolvency by Country (50% Sales Decline)



Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

In economic crisis, firms face financial distress due to collapse in demand. To simulate these conditions, we assume that firms experience a 50% reduction in their sales for the duration of the year. We then re-examine the distribution of z-scores by sector. Figure 4 presents each country's distribution of firms' financial health based on Altman's z-score ranges, under a hypothetical scenario of a 50% reduction in sales.

We observe a decrease in z-scores and a significant increase in the concentration of firms in the insolvency range of z-scores. Every sector saw an increase in this high-risk range of z-scores approaching 40%. As a robustness check we run the same exact scenario but with only a 25% sales reduction (not reported). In this case, each sector has more than 40% of its firms insolvent.

We next turn to the characteristics of firms that are exposed to financial distress in the event of a temporary (but protracted) collapse in sales (Table 3). Our results predict that a 1% increase in the number of a firm's Full Time Equivalent Workers increases that firm's z-score by 0.04 points even when controlling for product diversification and export reliance (column 1). Firm sales are also a highly significant indicator of health as a 1% increase predicts an increase of 0.08 points (column 2). Firm Age also appears significant at least at the 90% confidence level with a coefficient of 0.02 (column 3).

While export reliance appears to be significant when observed by itself, its significance is obscured when observed simultaneously with labor and sales, which can be explained by larger firms being more efficient and having the resources and infrastructure to export more. However, when observed with firm age, its coefficient remains robust, predicting a 1% increase in export reliance leading to a 0.15-point increase in z-score (fourth row, third column). Reliance on the Main Business Line for revenue is insignificant across all specifications (fifth row).

Table 3: Characteristics of Distressed Firms (Crisis Simulation, 50% Sales)

VARIABLES	(1) Z-Score	(2) Z-Score	(3) Z-Score
Log (Employment)	0.036***		
	(0.007)		
Log (Sales)		0.078***	
		(0.005)	
Log (Age)			0.019*
			(0.011)
Exports/Total Sales	0.081**	-0.044	0.149***
	(0.037)	(0.036)	(0.035)
MBL Concentration	0.051	0.041	0.054
	(0.048)	(0.048)	(0.048)
Constant	0.900***	-0.414***	0.945***
	(0.124)	(0.151)	(0.128)
Observations	6,656	6,656	6,650
R-squared	0.093	0.127	0.089
Country FE	YES	YES	YES
Industry FE	YES	YES	YES

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 34 countries with surveys in the past 5 years and with a sample size above 50 firms.

5. An Application to Africa

We now examine characteristics of distressed firms only within the 16 African countries in our sample and compare with the results in Table 3. For the 2,341 firms in this sub-sample, we observe from Table 4 that the results for the global sample still hold, but the magnitudes of each coefficient increase, suggesting an even larger Schumpeterian effect for African firms in the distressed sales environment. In column 1, we see that the coefficient on Log (Employment) is 0.02 points higher than in Table 3, as African firms on average have more employees. Column 1 also shows increased benefits of exporting in Africa when predicting firm stability in crisis. In column 2, we see approximately the same benefits of sale volume as in the global sample—with a 1% increase in sales predicting a 0.078-point increase in z-score—and the benefits of exporting continue to be obscured. In column 3, firm age continues to be a weakly significant indicator at the 90% significance level, but as with sales, the coefficient for Log (Age) is larger than in Table 3. Additionally, the benefits of exporting appear significantly larger in this specification with a statistically significant coefficient of 0.293. Concentration on the main business line continued to be insignificant as a determinant of financial health as it was for the global sample.

Table 4: Characteristics of Distressed African Firms (Crisis Simulation, 50% Sales)

	(1)	(2)	(3)
VARIABLES	Z-Score	Z-Score	Z-Score
Log (Employment)	0.0516***		
	(0.0133)		
Log (Sales)		0.0781***	
		(0.00837)	
Log (Age)			0.0334*
			(0.0186)
Exports/Total Sales	0.208***	0.0875	0.293***
	(0.0782)	(0.0757)	(0.0783)
MBL Concentration	0.110	0.121	0.0981
	(0.0865)	(0.0841)	(0.0866)
Constant	0.790***	-0.492**	0.844***
	(0.158)	(0.209)	(0.160)
Observations	2,341	2,341	2,339
R-squared	0.107	0.142	0.101
Country FE	YES	YES	YES
Industry FE	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 16 African countries with surveys in the past 5 years and with a sample size above 50 firms.

We next divide the 16 firms in the sub-sample into 3 regions: North Africa (Egypt, Jordan, Morocco, West Bank & Gaza), West Africa (Benin, Cameroon, Côte d'Ivoire, Gambia, Liberia, Mali, Sierra Leone), and South/East Africa (Kenya, Mozambique, Rwanda, Zambia, Zimbabwe). We rerun the analysis with interaction terms for each region (table 5). Column 1 shows the largest benefit for employment size coming in West African firms with a coefficient of 0.115. In column 2, each region's coefficient for Log (Sales) is highly statistically significant though their magnitudes are smaller. Finally, in column 3, we see a difference in the significance of firm age as a determinant of health by region. Older firms have a robust advantage in West Africa with a coefficient of 0.131, while other regions show little of this advantage.

Table 5: Region Characteristics of Distressed African Firms (Crisis Simulation, 50% Sales)

	(1)	(2)	(3)
VARIABLES	Z-Score	Z-Score	Z-Score
Log (Employment) x North Africa	0.0434***		
	(0.0126)		
Log (Employment) x West Africa	0.115***		
	(0.0219)		
Log (Employment) x South/East Africa	0.0319**		
	(0.0139)		
Log (Sales) x North Africa		0.0325***	
		(0.00512)	
Log (Sales) x West Africa		0.0410***	
		(0.00516)	
Log (Sales) x South/East Africa		0.0272***	
		(0.00489)	
Log (Age) x North Africa			0.0302*
			(0.0167)
Log (Age) x West Africa			0.131***
			(0.0292)
Log (Age) x South/East Africa			0.0161
			(0.0179)
Exports/Total Sales	0.182**	0.161**	0.261***
	(0.0792)	(0.0782)	(0.0807)
MBL Concentration	0.0213	0.0125	0.0183
	(0.0922)	(0.0904)	(0.0915)
Constant	0.953***	0.636***	1.008***
	(0.105)	(0.116)	(0.103)
Observations	2,341	2,341	2,339
R-squared	0.028	0.039	0.026
Industry FE	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: World Bank's Enterprise Surveys, https://www.enterprisesurveys.org/. The sample constitutes 16 African countries with surveys in the past 5 years and with a sample size above 50 firms.

Taken together, the evidence in Table 5 suggests that Schumpeter's theory of creative destruction in a distressed economic environment is particularly robust in Western Africa. Larger, older firms with more sales and high numbers of employees are predicted to fare considerably better than younger, smaller firms in this region.

6. Conclusions

Financial distress among private businesses comes as a consequence from economic crises. In a conservative scenario, we estimate that more than 60% of private companies could face such distress. The evidence on balance suggests that Schumpeter's theory of creative destruction in a distressed economic environment is particularly robust in Western Africa, but also holds true for a global sample of emerging and developing economies. Larger, older firms with more sales and high numbers of employees are predicted to fare considerably better than younger, smaller firms in the developing world.

The magnitude of the possible corporate insolvency may dictate government intervention, something Joseph Schumpeter would have no doubt disapproved.

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