In Search of Distress Risk in Emerging Markets

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1 Introduction

The last few years have seen increased concern about the deteriorating health of non-financial corporations in emerging markets . McKinsey & Company reported in February 2015 annual total debt growth of 5.3% and corporate debt growth of 5.9% between 2007 and 2014. Standard & Poor's data shows global debt to earnings ratios at 12-year highs, a result of both higher debt and the effect of weak global demand and lower commodity prices on revenues. The consequences of these poor solvency conditions are starting to show. Moody's reported on March 1^{st} that global corporate defaults had reached their peak since the Global Financial Crisis (GFC). Furthermore, the rating agency forecasted a 30% year-over-year increase in speculative-grade defaults by the end of 2016.

Even though corporate fragility has expanded worldwide, emerging markets (EMs) appear most compromised. The International Monetary Fund raised a flag about EM corporate leverage in its 2015 Global Financial Stability Report, which shows the quadrupling of EM corporate debt levels between 2004 and 2014. The report warns about the quality of the firms holding the debt, noting that the share of debt held by troubled firms is the highest in over a decade. Moreover, it shows that EM corporate debt constitutes a significant part of domestic bank assets - as much as 50% or more of total loans for eight EMs.

Currency denomination of the debt is another source of concern. The sharp appreciation of the U.S. dollar has added extra pressure on NFCs with large liabilities denominated in the greenback. Avdjiev et al. (2015) document that borrowers residing in emerging markets account for over a third of global dollar credit to non-banks outside the U.S. and that dollar bond issuance doubled between 2009 and 2015. Bruno and Shin (2016) use BIS data to show that issuance of international debt securities in foreign currency by NFCs rose from \$3 billion in Q1 2001 to over \$60 billion in Q1 2015, \$51.6 billion of which were denominated in U.S. dollars. Research on the drivers and consequences of high currency exposure has been limited due to the shortage of accurate data on currency composition.[1] However, the view most widely held is that foreign-currency liabilities are in fact a concern for EM NFCs – and particularly troubling for firms that do not have natural currency hedges in place (e.g. firms in non-tradable industries).[2] Harvey and Roper (1999) show that high foreign currency-denominated leverage and low profitability were important factors spreading the East Asian Financial Crisis. Dell'Ariccia et al. (2015) corroborate the idea that foreign currency borrowing increases systemic risk and exposes lenders to the risk of default when the borrower's currency plunges.

Many also find the recent surge in offshore borrowing troublesome. Bruno and Shin (2016) show that more than 50% of NFC international debt securities since 2010 have been issued by offshore affiliates of NFCs in EMs. The implication is that large NFCs are acting as financial intermediaries, as they borrow from abroad and funnel the funds into their local

[1] The two major issues compiling accurate data on debt currency composition are: 1. Many corporate reports present the currency composition of their liabilities in the notes of the reports and not in hard data, and 2. the use of offshore intermediaries to borrow funds makes it difficult to establish the residence of the ultimate debt-holder (a problem documented in Shin and Zhao (2013) and Avdjiev et al. (2014) among others).

[2] Kalemli-Ozcan et al. (2015) and others find that currency exposure is not as risky for companies with natural hedges.

economies.

This cross-border financial activity of NFCs presents several dangers in addition to the obvious foreign currency risk. First, Bruno and Shin (2016), Caballero et al. (2015), and Avdjiev et al. (2014) express concerns about NFCs using leverage for speculative activities, since it exposes them more directly to market conditions. Second, Chui et al. (2014) suggest that since larger, more creditworthy EM NFCs have access to international markets, local banks end up lending to smaller, riskier firms than they otherwise would. Bruno and Shin (2016) concur – the carry trades performed by EM NFCs help channel international funds into their local economies, expanding the supply of credit and easing funding conditions for smaller, riskier domestic borrowers.[3] Third, Avdjiev et al. (2014) suggest that offshore intermediaries play a role in evading capital controls and transmitting external macroeconomic conditions into the domestic financial system. Last, since the regulations on non-banks are not as strict as those on banks, NFCs are likely to engage in riskier lending practices than their financial counterparts.

Other papers focus on specific financial sheet variables to identify corporate malaise. Alfaro et al. (2016) use firm-level data to show that corporate fragility is currently less severe but more widespread in EMs than during the build-up of the East Asian Financial Crisis (EAFC). The authors emphasize today's higher liquidity needs (measured by current over total liabilities), weaker solvency positions (lower interest coverage ratios), and lower return on invested capital. They show that high corporate leverage following the Global Financial Crisis is more widespread than in the pre-EAFC period. However, no country has debt levels as high as the troubled East Asian nations in the mid-1990s. A deeper analysis reveals that the positive correlation between leverage and corporate fragility strengthens under times of local currency devaluations and low economic growth.

Chui et al. (2014) and Bruno and Shin (2016) also focus on firms' balance sheets, as they point out the increase in cash holdings among NFCs in EMs. Both papers argue that firms are not accumulating cash as a precautionary measure, but to engage in cross-border speculative activities (i.e. to take advantage of interest rate spreads). Hence, the traditional belief that cash increases a firm's repaying ability may not hold in this environment.

All these concerns are exacerbated by the global monetary outlook. The IMF is one of many to point out that a reversal of global monetary conditions is a key risk for the emerging market corporate sector. Higher interest rates in advanced economies reduce the premium and carry on EM assets, lowering the demand for debt securities and making liabilities pricier to roll-over. In addition, as the U.S. dollar rises in response to the higher U.S. rates, dollar-denominated liabilities in EMs would grow in local currency terms. Powell (2014) shows similar concerns about global debt paired with other macro conditions. In particular, the report warns about the risk of asset price drops, currency depreciations, and a fall in Chinese demand for raw materials damaging the repaying ability of NFCs in EMs.

The first purpose of this project is to explore the determinants of corporate bankruptcy risk in emerging markets – the accounting ratios, market variables, and macroeconomic data policymakers should pay attention to if concerned about widespread defaults. In addition

[3] Hattori et al. (2009) argue that this is exactly what happened in Japan in the 1980s. When international markets opened to large NFCs, banks were forced to target riskier sectors for their lending (e.g. real estate), resulting in a huge financial asset bubble and ensuing 'lost decade'.

to their particularly fragile status, a number of fundamental idiosyncrasies of EMs justify a specific approach to analyze their corporate health. First, Mendoza and Terrones (2008) find that corporate credit booms in EMs are followed by larger macroeconomic responses (such as drops in output, investment, and consumption) than in advanced economies. The authors also show that credit expansions are determined by different factors in the two regions: financial reforms and productivity gains in advanced economies and large capital inflows in EMs. Second, an extensive literature on capital flows suggests that emerging markets have higher liquidity risks than advanced economies.[4] Third, EMs have larger exposure to currency risk, since around 80% of outstanding EM bonds are denominated in a foreign currency (largely the U.S. dollar).[5]

This paper contributes to the existing corporate default literature in three ways. First, it determines precisely which accounting, financial market, and macroeconomic variables are associated with corporate default risk in emerging markets – and compare them to those in advanced economies. Second, it improves the current tools to predict corporate distress in emerging markets. Instead of simply estimating US-based models using emerging market data, my specification includes the set of explanatory variables that specifically maximizes predictive power for emerging markets.

The second purpose of this paper is to study the pricing of financially distressed firms in emerging markets. Asset pricing theory suggests that investors should demand a premium for holding stocks with high distress risk. However, Campbell et al. (2008 and 2011) show this does not hold true in the United States. I use the probability of failure measure developed in the first part of the paper to explore the performance of distressed stocks between 1995 and 2016.

The rest of the paper is organized as follows. Section 2 explores the literature on the determinants of corporate default, following its progression from correlations between individual accounting ratios and bankruptcy to hazard models that include accounting, market, and macroeconomic data to estimate firms' likelihood of default. Section 3 describes the data. Section 4 explains the model and variable selection methodology and presents some early results. Section 5 discusses my next steps.

2 Determinants of Corporate Default Literature

Debt levels have typically received the bulk of the attention in the analysis of corporate health and prediction of corporate default. However, several studies have shown the importance of other variables in forecasting default. Edward Altman developed the most influential measure of corporate default risk in 1968, the Z-score.[6] Before his work, the literature on corporate bankruptcy predictors was developed almost exclusively using univariate methods, i.e. focusing on just one ratio at a time to estimate the probability of corporate failure.[7]

[4] See Koepke (2015) for a survey of the empirical EM capital flows literature.

[5] World Bank data.

[6] See Altman (1968).

[7] Beaver (1966) was the first to use multiple accounting ratios to predict bankruptcy, but he simply investigated if specific ratios were good predictors of failure by comparing them in bankrupt and non-bankrupt firms.

Altman hypothesized that using multiple variables simultaneously would improve the accuracy of previous studies. From a starting list of 22 accounting ratios used in prior research, Altman found a set of five ratios and coefficients that best predicted bankruptcy for his 66 U.S. manufacturing firms (33 bankrupt) and 20 years of data. The measure that results from combining them is known as Altman's Z-Score, and it decreases in the probability of bankruptcy:

$$Z = .012X1 + .014X2 + .033X3 + .006X4 + .999X5$$

where $X1$ = working capital to total assets, $X2$ = retained earnings to total assets, $X3$ = EBIT to total assets, $X4$ = market value of equity to book value of total liabilities, and $X5$ = sales to total assets.

Altman uses Multiple Discriminant Analysis (MDA). to estimate the linear combination of the independent variables that best discriminates between the dependent variable's categories. Since the dependent variable categories Altman uses are "bankrupt" and "non-bankrupt", the resulting set of characteristics and coefficients can be used to measure the probability of bankruptcy.

Houghton and Woodliff (1987) perform a similar analysis to Altman (1968), using Discriminant Analysis on a set of 12 bankrupt and 36 non-bankrupt firms. While looking for determinants of corporate success, they find another determinant of corporate failure overlooked by Altman: low dividends to earnings.

Both papers mentioned so far perform their analysis on small sample sizes. Ohlson (1980) aimed for more robust conclusions using a dataset of 105 bankrupt and 2,058 non-bankrupt firms. More importantly, the author used a likelihood estimation of a conditional logit model instead of the hitherto more common Multivariate Discriminant Analysis to get around some of the econometric problems associated with MDA.[8]

The results from Ohlson's estimation show that corporate default is associated with small firm size, low net income to total assets, high total liabilities to total assets, and low working capital to total assets. However, when testing his predictive model, the author found that it is unable to match the predictive power of Altman's (1968)—85% prediction rate in-sample compared to Altman's 95% for bankrupt firms.

Most models up to this point were static in the sense that they ignored a firm's behavior over time when estimating its probability of bankruptcy. Shumway (2001) points out that in order to use a static model effectively researchers must have a very long time-span of data. They must also choose arbitrarily how long ahead of bankruptcy to observe the firms' characteristics—adding selection bias to the process. Shumway's (2001) main contribution was estimating a hazard model, which enabled him to "use all available information to determine each firm's bankruptcy risk at each point in time". By including each firm-year as a separate observation, the amount of data used for estimation is much larger (ten times larger if we have ten years of data) than in static models. This allows the researcher to control for "period at risk"—the fact that some firms fail after being at risk for many years and others go from healthy to bankrupt much faster. It also allows explanatory variables to

[8]MDA assumes equal variance-covariance matrices for both default and non-default groups of firms; the estimation output is an ordinal ranking with little economic interpretation; and bankrupt and non-bankrupt firms in the studies are matched based on some arbitrary characteristics (e.g. size, industry), instead of incorporating those characteristics into the model as predictors of default.

change with time, providing a picture of a firm's changing health.

Another contribution of Shumway (2001) was combining accounting and equity market variables. The set of variables with highest forecasting power in his testing is comprised of market size, past stock returns, idiosyncratic standard deviation of stock returns, net income to total assets, and total liabilities to total assets.

Chava and Jarrow (2004) improve forecasting by shortening the observation intervals to monthly frequency. They also prove the existence of an industry effect and show that transportation, communication, utilities, manufacturing, and minerals are less sensitive to low net income to total assets and more sensitive to high leverage than other industries. One more contribution the authors make is to validate Shumway's hazard model by showing that it outperforms Altman's (1968) and Zmijewski's (1984). 86.4% of the firms Shumway's model places in the two deciles most likely to fail are indeed firms that go bankrupt. This is compared to the 77.6% and 43.2% identified by Altman's and Zmijewski's models, respectively.

Campbell et al. (2008) build on the work of Shumway (2001). Their paper uses 1963-2003 US data (1.7 million firm-months) to show that firms are more likely to enter distress if they have higher leverage, lower profitability, lower market capitalization, lower past stock returns, more volatile past stock returns, lower cash holdings, higher market-book ratios, and lower prices per share.[9] The authors use Shumway's (2001) specification as base and make modifications that improve the model's predictive power. First, they divide net income and leverage (both explanatory variables) by market value of assets instead of book value. Second, they add corporate cash holdings, Tobin's Q, and price per share to the set of explanatory variables. Third, they study default forecasts at different horizons, finding market capitalization, market-book ratio, and equity volatility the most consistently predictive characteristics of corporate distress, and demonstrating the increased importance of balance sheet versus market variables as the horizon increases.

Finally, Campbell et al. (2008) study the asset pricing implications of their results using their fitted probability of failure as a measure of financial distress. Their main finding is that stocks of distressed companies experience abnormally low returns.

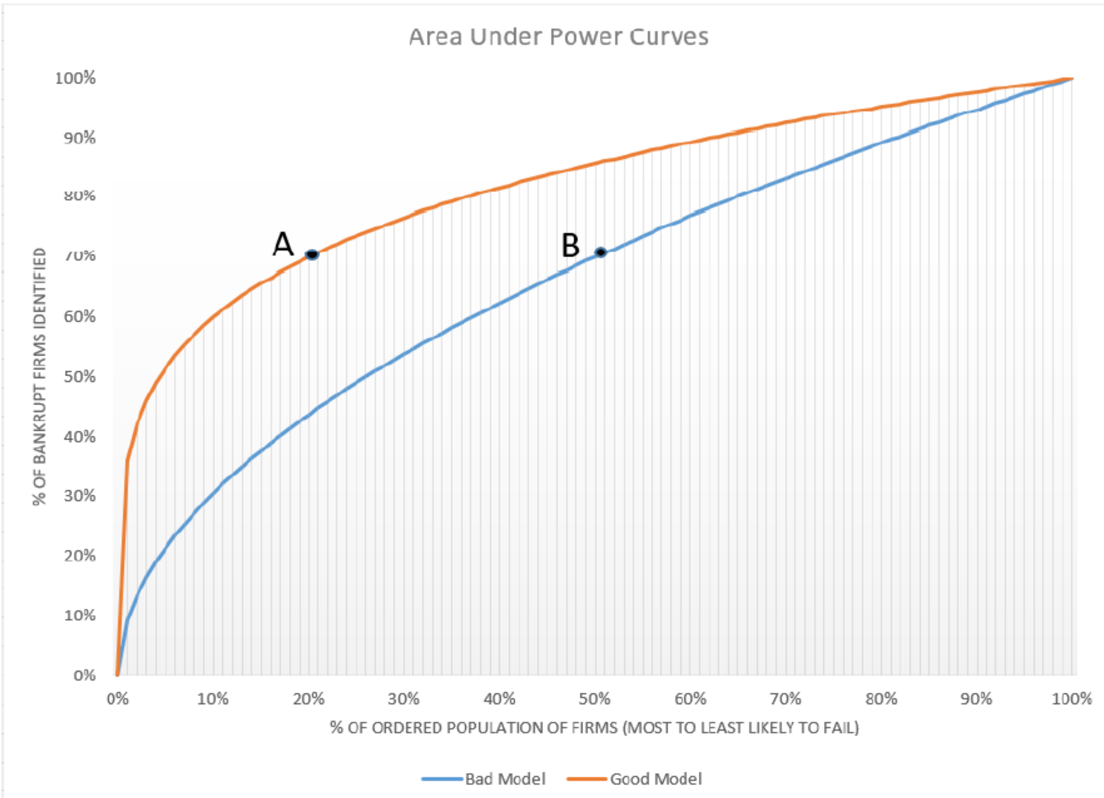
The literature up to this point includes several different specifications. Wu et al. (2010) perform a comprehensive evaluation of the performance of the different models (MDA, probit, standard logit, and hazard) using different data (accounting variables, market data, and firm characteristics like size and corporate diversification). They find that the predictive power of models varies through time, suggesting that each is capturing a different aspect of corporate fragility. Their two main results are that a model that integrates accounting and market variables outperforms all others in forecasting ability, and that the hazard model chosen by Shumway (2001) outperforms its methodological counterparts.

To measure a model's forecasting ability, the authors rely on Pseudo-R^2 and the Receiver Operating Characteristics (ROC) score. The ROC score, also known as "area under the power", is computed using the cumulative fraction of defaults as a function of the ordered population of firms (from most to least likely to fail as predicted by the model). Figure 1 shows an example. Point A on the plot tells us that the 20% of firms that a particular model identifies as most likely to default include 70% of the firms that end up going bankrupt. On the other hand, point B signals that not until the fifth decile of firms (ordered from most to

[9] The authors define distress as either filing for bankruptcy, getting delisted, or receiving a D rating.

least likely to default) does the model identify 70% of bankrupt companies. The ROC score is the area under the curve, so a larger area indicates that the model is correctly predicting more bankrupt firms as being likely to fail. The score ranges between 0.5, indicating no discriminatory power, and 1, implying perfect identification of bankrupt and healthy firms.[10] Wu et al. (2010) report ROC scores of 0.86, 0.89, 0.85, and 0.91 for Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001) respectively.

Figure 1: Receiver Operating Characteristics



All the research mentioned so far uses only U.S. data. I wrote in the introduction about the idiosyncrasies of EMs and the need to tailor research accordingly when using EM data. There is therefore value in studying the determinants of corporate default specifically in EMs. Any data limitations that prevented this from being done in the past no longer hold. The next subsection presents the few research studies that use non-U.S. data, with the following purpose. First, to show that no bankruptcy prediction work has been done on a comprehensive dataset of EMs using a hazard model like in Campbell et al. (2008). And second, to consider their explanatory variables of choice as potential determinants of corporate default in EMs.

[10]Source for ROC score: Sobehart and Keenan (2001).

2.1 Non-U.S. Bankruptcy Prediction Literature

Pomerleano (1998) uses accounting ratios to study the build-up of the East Asian Crisis, finding excess leverage and poor capital performance in the years leading up to the crash. The author uses the following measures to study corporate health: leverage, debt sustainability, liquidity, profitability, tangible fixed assets growth and their financing, corporate vitality (Tobin's Q), and financial fragility (Altman's Z-score). His data shows a dramatic increase of fixed assets financed largely by debt, as well as levels of short term debt much higher than in developed economies. He also finds a big drop in capital performance in the time period analyzed, in addition to much higher returns on equity and book-to-market ratios in Asia than in developed countries.

To adjust his Z-Score to the different environment in EMs – and instruct on its applicability – Altman (2005) introduces the Z" model and corresponding Emerging Market Scoring system.[11] The paper provides steps on how to adjust his credit rating model to each country using Mexico as a guide. These steps include reducing the score if the company is overly vulnerable to currency risk, belongs to a risky industry, or is not in a dominant position in such industry. The resulting Z"-Score has different coefficients than the original Z-Score but the same predictors:

$$Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25$$

Kordlar and Nikbakht (2011) apply a slight variation of Shumway's (2001) model to the Tehran Stock Exchange. Their choice of variables outperforms Shumway's, but they are all borrowed from other U.S.-based studies. The authors make no effort to adapt the variable set to Iran's idiosyncrasies.

Xu and Zhang (2009), on the other hand, modify their variable set to match the characteristics of their target market – Japan. Adding a measure of dependence on banks and business groups (known as Keiretsu) improves the predictive power of their model, which the authors test on 3,510 listed firms (76 bankrupt) between 1992 and 2005. But they also show that the established models for prediction of U.S. bankruptcy can be safely applied to Japanese firms, since their resulting coefficients on the variables have the same sign and statistical significance as when applied to U.S. data.

Agarwal and Bauer (2013) test the predictive power of several models on a set of NFCs listed in the London Stock Exchange between 1979 and 2009. The authors find that the hazard model in Shumway (2001) and Campbell et al. (2008) has a higher ROC score than accounting-only specifications and structural models (0.90 versus 0.84 and 0.87 respectively).

Hernandez Tinoco et al. (2013) use a dataset of 23,218 firm-year observations of companies listed in the United Kingdom between 1980 and 2011. Notably, they add macroeconomic variables to the standard hazard bankruptcy prediction model. The authors find that the model which includes all types of variables has higher explanatory power than models that include combinations of one or two types of variables (i.e. accounting and macro, market and macro, market only, or accounting only). It also achieves a higher ROC score when used to predict default. The following are the one-year determinants of corporate distress they find: low EBIT to total liabilities, high total liabilities to total assets, low working capital to

[11] More information on the specifics of the Z" model derivation can be found in Altman (2005).

Default	
Action Type	**Subcategory**
Bankruptcy filling	Administration, Arrangement, Canadian CCAA, Chapter 7, Chapter 11, Chapter 15, Conservatorship, Insolvency , Japanese CRL, Judicial Management, Liquidation, Pre-Negotiation Chapter 11, Protection, Receivership, Rehabilitation, Rehabilitation (Thailand 1997), Reorganization, Restructuring, Section 304, Supreme court declaration, Winding up, Work out, Sued by creditor, Petition Withdrawn, Other
Delisting	Bankruptcy
Default Corporate Action	Bankruptcy, Coupon & Principal Payment, Coupon Payment Only, Debt Restructuring, Interest Payment, Loan Payment, Principal Payment, ADR (Japan only), Declared Sick (India Only), Regulatory Action (Taiwan only), Financial Difficulty and Shutdown (Taiwan only), Buyback option, Other

Figure 2: Reasons for default

daily operating expenses, low interest coverage, high inflation, high interest rates, low equity price, low residual returns, low relative market capitalization, and low market capitalization to total debt.

Two other notable conclusions from their study are related to the effect of the macroeconomic variables to firm default. First, the size of the inflation and interest rate coefficients is small relative to those of the accounting and market variables. This indicates that they have a smaller effect on firms' likelihood of failure. Second, the addition of macroeconomic variables results in a tiny improvement in the model's predictive power with a one-year horizon. Their contribution even turns negative when predicting two years in advance – the ROC score decreases when adding macroeconomic variables to the accounting-only model.

3 Data

The majority of the data I use for this study is from the Risk Management Institute (RMI) at the National University of Singapore, generously provided to me as part of their Credit Research Initiative. The RMI dataset contains detailed bankruptcy, accounting, and market data for over 60,000 exchange-listed firms in 119 countries between 1990 and 2016. The countries I include in my analysis are those classified as Emerging Markets by MSCI during the majority of my sample period (1990-2016): Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Jordan, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, Turkey, and Vietnam. For comparison purposes, I will also use data from the United States.

Since market data is fairly accessible, the value of this dataset resides in the broad coverage of financial statement data and, especially, of monthly bankruptcy-like events. As Figure 2 shows, I have access to detailed information about a company's reason for default. This is important because different countries have different definitions of default. I classify in the Default group any firm in the Bankruptcy filing and Delisting categories, as well as those in the Default Corporate Action - Bankruptcy group.

Figures 3 and 4 show the number of firms and defaults in my sample, by country and year.

Figure 5 shows the set of variables I use in the variable selection part of the exercise.

Year	AR	BR	CL	CN	CO	CZ	EG	HU	IN	ID	JO	MY	MX	MA	PK	PE	PH	PL	RU	ZA	KR	TW	TH	TR	US	VN	Total	Total-exUS
1990	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,946	0	2946	0
1991	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5,553	0	5553	0
1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6,942	0	6942	0
1993	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8,213	0	8213	0
1994	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9,213	0	9213	0
1995	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	18	0	9,976	0	10006	30
1996	0	10	0	0	0	0	0	0	0	0	0	0	146	0	0	0	0	0	0	0	0	9	328	0	10,874	0	11367	493
1997	30	27	6	0	0	0	0	0	0	0	0	0	247	0	0	0	0	0	0	0	0	10	442	18	11,997	0	12777	780
1998	45	40	373	0	0	0	0	0	0	0	0	2	278	0	0	0	0	0	0	1	0	12	1,186	32	12,055	0	14024	1969
1999	62	57	466	0	0	0	0	0	0	0	0	266	278	0	0	0	154	0	0	22	3	12	1,427	87	12,308	0	15142	2834
2000	172	385	510	0	0	0	0	0	2	36	0	2,037	474	0	0	0	220	62	0	38	8	251	1,429	816	34,570	0	41010	6440
2001	206	481	485	0	0	0	0	0	14	340	0	2,400	494	0	0	0	228	324	0	45	24	835	1,727	1,330	42,091	0	51024	8933
2002	119	526	457	4,218	2	12	0	18	29	473	0	2,552	479	0	0	11	222	414	0	59	8,339	1,043	1,979	1,370	38,762	0	61084	22322
2003	93	585	468	4,978	1	47	0	29	21	534	0	2,512	483	0	0	10	233	481	0	76	10,798	1,121	2,199	1,293	36,473	0	62435	25962
2004	190	637	466	7,829	17	104	0	103	11	802	0	5,183	537	0	0	23	233	1,002	0	66	11,656	1,199	2,343	1,360	35,483	3	69247	33764
2005	340	763	643	8,109	114	130	0	142	16	926	24	5,849	510	0	13	189	283	1,365	0	56	11,835	1,323	2,389	1,750	35,199	43	72011	36812
2006	382	873	931	7,850	123	107	388	142	18	1,025	36	6,324	560	0	200	229	295	1,505	0	57	12,187	4,800	2,592	2,036	34,075	149	76884	42809
2007	471	1,259	1,007	9,735	127	78	604	120	50	1,302	73	6,737	599	0	716	367	357	1,802	0	61	12,934	5,226	2,817	2,082	33,148	991	82663	49515
2008	436	1,418	1,120	10,833	143	76	711	131	80	1,393	110	5,326	541	0	509	293	806	2,284	0	72	13,520	6,250	2,817	2,029	32,572	1,636	85106	52534
2009	414	1,425	1,160	11,584	129	70	1,488	172	171	1,399	366	5,104	607	0	1,163	265	888	2,449	0	65	13,687	7,165	2,799	2,050	31,203	2,004	87827	56624
2010	413	1,524	1,113	13,291	180	69	1,190	186	746	1,724	450	5,993	622	0	1,591	289	974	2,597	0	94	13,368	7,334	3,148	2,059	30,354	2,904	92213	61859
2011	432	1,592	1,241	16,547	193	64	1,064	125	5,532	2,033	364	5,900	608	0	1,335	327	1,081	2,844	0	93	14,418	7,620	3,121	2,188	30,171	4,320	103213	73042
2012	358	1,501	1,217	18,347	177	61	1,216	144	10,213	2,237	345	5,822	637	0	1,436	270	1,254	2,851	0	84	10,610	8,203	3,274	2,362	29,782	4,340	106741	76959
2013	353	1,745	1,252	18,715	137	41	1,200	172	12,579	2,445	490	5,837	655	0	1,047	224	1,217	2,929	0	81	16,571	6,852	3,501	2,434	29,611	4,300	114388	84777
2014	412	1,802	1,183	17,938	195	58	1,185	187	10,744	2,511	621	5,981	623	0	1,039	210	1,381	2,929	0	105	17,139	6,841	3,719	2,450	30,582	4,999	114834	84252
2015	403	1,745	1,166	17,725	183	52	1,129	199	6,753	2,566	935	5,770	647	0	1,030	201	1,497	2,997	0	72	18,549	6,893	4,000	2,485	31,391	5,078	113466	82075
2016	357	1,213	948	16,939	160	53	859	110	4,684	2,167	777	4,463	535	0	725	179	1,351	2,449	0	39	15,110	5,715	3,245	2,069	25,035	3,808	92990	67955
Total	5688	19608	16212	184638	1881	1022	11034	1980	51663	23913	4591	84058	10560	0	10804	3087	12674	31284	0	1186	200756	78726	50500	32300	650579	34575	1523319	872740

Figure 3: Number of firm-months with total assets and monthly return data

Year	AR	BR	CL	CN	CO	CZ	EG	HU	IN	ID	JO	MY	MX	MA	PK	PE	PH	PL	RU	ZA	KR	TW	TH	TR	US	VN	Total	Total-exUS
1990	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1991	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	4	0
1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
1994	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0
1995	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0
1996	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	4	0
1997	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	7	0	8	1
1998	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	8	0
1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	9	0	10	1
2000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0	22	0
2001	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	24	0	27	3
2002	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	20	0	23	3
2003	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	4	0	11	0	18	7
2004	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1	0	12	0	17	5
2005	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	8	0	10	2
2006	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	1	0	4	0	8	4
2007	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	4	0	2	0	3	0	10	7
2008	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	1	0	10	0	16	6
2009	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	2	0	2	0	2	0	8	6
2010	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	2	0	2	0	8	6
2011	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	1	0	0	2	0	6	4
2012	0	2	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	2	0	1	0	4	0	13	9
2013	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3	0	0	0	0	0	5	5
2014	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	2	0	9	7
2015	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	1	0	1	0	8	7
2016	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	1	0	0	0	0	0	0	0	1	0	5	4
Total	1	4	0	9	0	0	0	0	0	2	0	11	7	0	0	0	1	3	0	1	29	1	18	0	167	0	254	87

Figure 4: Number of defaults for firm-months with total assets and monthly return data

Variable	Description	Variable	Description
ex_ret	log (1 + Monthly Return) - log (1 + Index Monthy Return)	asset_tang	Plant, Property and Equipment / Total Assets
price_monthC	log (Price)	ebit_totAsset	EBIT / Total Assets
vol_return	1-month Volatility of Returns	div_earn	Dividends / Net Income
rel_size	log (Market Cap/Country's Total Market Cap)	curAsset_curLiab	Current Assets / Current Liabilities
nita	Net Income / Total Assets	deltaNet_Income	log (Net Income / Net Income[t-1])
nimta	Net Income / (Market Cap + Total Liabilities)	curLiab_totLiab	Current Liabilities / Total Liabilities
tlta	Total Liabilities / Total Assets	gdpGrowth	log (Nominal GDP in USD[t] / Nominal GDP in USD[t-1])
tlmta	Total Liabilities / (Market Cap + Total Liabilities)	inflation	log (CPI[t] / CPI[t-1])
cashta	Cash / Total Assets	deltaRER	log (Real Exchange Rate[t] / Real Exchange Rate[t-1])
cashmta	Cash / (Market Cap + Total Liabilities)	RIR	Real Interest Rates
mb	Market Cap / Book Value of Equity	UR	Unemployment Rate
retEarn_totAsset	Retained Earnings / Total Assets	ToT	Terms of Trade
mktEq_bookLiab	Market Cap / Total Liabilities	comp_risk_rating	ICRG Composite Risk Rating
rev_totAsset	Revenue / Total Assets	corruption	ICRG Corruption Index
workCap_totAsset	Working Capital / Total Assets	econ_risk	ICRG Economic Risk
ebit_intExp	EBIT / Interest Expense	offsh_issue	Country's Offshore Bond Issuance
ppe_change	Plant, Property and Equipment[t] - Plant, Property and Equipment[t-1]	credit_nonBank	Credit to country's Non-Banking Sector

Figure 5: Description of the 34 market, accounting, and macroeconomic bankruptcy predictors used in the variable selection analysis

Many of them were found to be significant determinants of corporate default in the literature, and I chose others that measure some of the EM-specific risks discussed in the introduction.

3.1 Summary Statistics

Figure 6 reports the summary statistics for the 34 variables I use in the variable selection exercise. The left-hand panel describes the entire sample, while the right-hand panel contains information only for the 87 firms that comprise the Default group. When calculating these summary statistics, I weigh each firm equally.

The coloring on the table helps portray the differences between the two groups. The only three categories where Default group averages are higher than sample averages are volatility of returns, leverage, and real interest rates. High volatility returns has been established as a good predictor of corporate distress in the literature, while both leverage and high interest rates hurt firms' solvency and funding conditions.

The set of variables with lower values in the Default group matches what one would expect. Firms on the brink of default exhibit lower excess returns, smaller size, lower and worsening profitability, lower cash holdings, smaller investment, and worse solvency. Stock price and market/book ratio are also lower for the Default group but by less than 10%, hence their lack of color. Somewhat surprisingly, Current to Total Liabilities is lower for the Default group.

4 Methodology

I divide the sample of firms into two groups: firms that default during the sample period ("bankrupt") and firms that remain healthy throughout ("non-bankrupt"). To measure the probability that a firm will belong to the bankrupt group next month, the dependent variable in the model is a binary variable Y, where $Y_{i,t} = 1$ in the month t that firm i going bankrupt and $Y_{i,t} = 0$ everywhere else. Firms disappear from the sample after they default. Firms which leave the sample for reasons other than bankruptcy (e.g. merger or delisting) do not have $Y_{i,t} = 1$ on the month of their departure.

Following the work of Shumway (2001), Chava and Jarrow (2004), Campbell et al. (2008), and others, I estimate a dynamic panel model using a logit specification. Shumway (2001) proves that estimating a multi-period logit model is equivalent to estimating a discrete-time hazard model, which allows explanatory variables to vary through time and increases the number of observations by the number of time periods in the sample compared to a static logit model. He also shows that single-period logit approaches can yield biased, inefficient, and generally inconsistent estimates, and that the hazard model overcomes these econometric problems. To estimate a hazard model in a logit framework, each firm-month is included as a separate observation. Hence, each bankrupt firm only contributes one default observation, and has $y_{i,t} = 0$ for all periods in which it is healthy. The set of explanatory variables is comprised of data from all firms and periods up to the period where firms default or exit the sample. When computing test statistics, the correct number of observations must be set to the number of firms and not the number of firm-month, given that the firm-period observations can't be assumed to be independent.

	All Firm-months					Defaults				
Variable	Obs	Mean	Std.Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max
ex_ret	857,114	0.04228	0.12151	-0.203902	0.28583	87	0.0257	0.12908	-0.203902	0.28583
price_monthC	872,740	4.04319	3.07798	-0.553385	8.81284	87	3.74102	3.41771	-0.553385	8.81284
vol_return	868,716	0.02746	0.01811	7.87E-09	0.09681	87	0.03154	0.02042	7.87E-09	0.09681
rel_size	715,350	-6.9587	2.59084	-1.48E+01	-2.8575	83	-6.8087	2.21541	-1.13E+01	-2.8575
nita	871,870	0.00676	0.02266	-0.079153	0.04305	87	0.00201	0.02553	-0.079153	0.04305
nimta	871,870	0.00577	0.01862	-0.05294	0.03706	87	0.00236	0.01951	-0.05294	0.03706
tlta	872,740	0.42922	0.21121	0.085542	0.84491	87	0.5353	0.20264	0.119416	0.84491
tlmta	872,740	0.41649	0.26941	0.035172	0.9035	87	0.52608	0.25664	0.079989	0.9035
cashta	871,744	0.09552	0.09609	0.002606	0.37318	87	0.06676	0.07723	0.002606	0.37027
cashmta	871,744	0.0788	0.07937	0.001892	0.29122	87	0.06614	0.0743	0.001892	0.29122
mb	872,740	1.72354	1.53159	0.222646	6.78347	87	1.64253	1.67125	0.222646	6.78347
retEarn_totAsset	756,380	0.12946	19.5096	-203.226	8197.35	77	-0.1123	0.82651	-5.180841	0.61492
mktEq_bookLiab	872,705	34.2313	3255.85	-1236.144	1700459	87	1.83158	2.42111	0.031976	11.5017
rev_totAsset	868,812	1.03138	373.482	-59.22626	205112	87	0.1952	0.12111	0.000155	0.5794
workCap_totAsset	870,094	0.1597	0.27659	-9.736059	1.47827	87	0.05042	0.354	-2.143261	0.59759
ebit_intExp	598,929	691.626	65440.9	-2847975	2.29E+07	76	41.1117	207.09	-80.9149	1738.93
ppe_change	524,436	1137.89	195812	-4.23E+07	3.95E+07	49	-2201.3	15370.4	-107569.6	1744.7
asset_tang	608,641	0.56775	5.53971	-0.258341	1101.96	54	0.61157	0.38759	0.039458	1.68455
ebit_totAsset	870,735	0.01141	0.02153	-0.061401	0.05328	87	0.0096	0.01935	-0.061401	0.05328
div_earn	95,071	0.08281	0.22961	0	0.80363	16	0	0	0	0
curAsset_curLiab	869,869	22.3349	1533.68	-20.57968	269382	87	1.64581	1.5667	0.032007	9.80618
deltaNet_Income	763,386	0.00547	0.2253	-0.579925	0.61877	78	-0.0122	0.22927	-0.579925	0.61877
curLiab_totLiab	870,088	0.73304	0.23165	0.155854	1	87	0.65142	0.21993	0.195977	1
gdpGrowth	771,660	0.0797	0.09569	-0.986979	0.41482	83	0.06842	0.09577	-0.193683	0.25406
inflation	749,950	0.03392	0.03694	-0.011737	0.61955	83	0.03395	0.0345	-0.009045	0.19358
deltaRER	749,950	0.007	0.0617	-0.78971	0.27343	83	0.00268	0.06249	-0.197619	0.14518
RIR	635,633	4.02182	6.10503	-18.32711	77.6173	79	4.60411	7.02751	-4.122577	48.34
UR	769,259	4.74179	2.68054	0.658	27.8	83	3.81463	2.78748	0.675	22.525
ToT	605,065	90.475	25.7881	50.19265	242.998	72	88.0194	22.8176	50.19265	170.276
comp_risk_rating	872,740	74.848	6.34211	47.75	87.3	87	75.054	5.50239	57	83.75
corruption	872,740	2.51111	0.53062	1	4.5	87	2.3046	0.52472	1	3
econ_risk	872,740	38.9374	3.92723	17.5	45	87	39.3391	3.26405	30.5	43.5
offsh_issue	813,290	27310.5	56271.1	-4278	279678	85	20796.8	48416	-1157	264384
credit_nonBank	473,963	5402.53	7834.54	79.892	26001.1	53	3073.56	6737.64	154.962	26001.1

Figure 6: Summary statistics for all firm-months and for the Default group. Green indicates that the value for the default group was larger than 1.1 times the value of the entire sample. Red indicates that the value for the default group was smaller than 0.9 times the value of the entire sample.

I assume that the marginal probability of default over the next period follows a logistic distribution of the form:

$$P_{t-1}(Y_{i,t} = 1) = \frac{1}{1 + exp(-\alpha - \beta x_{i,t-1})}$$

where $Y_{i,t}$ is an indicator that equals one if the firm defaults in period t, and $x_{i,t-1}$ is a vector of explanatory variables known at the end of the previous period. A higher level of $\alpha + \beta' x_{i,t-1}$ implies a higher probability of default.

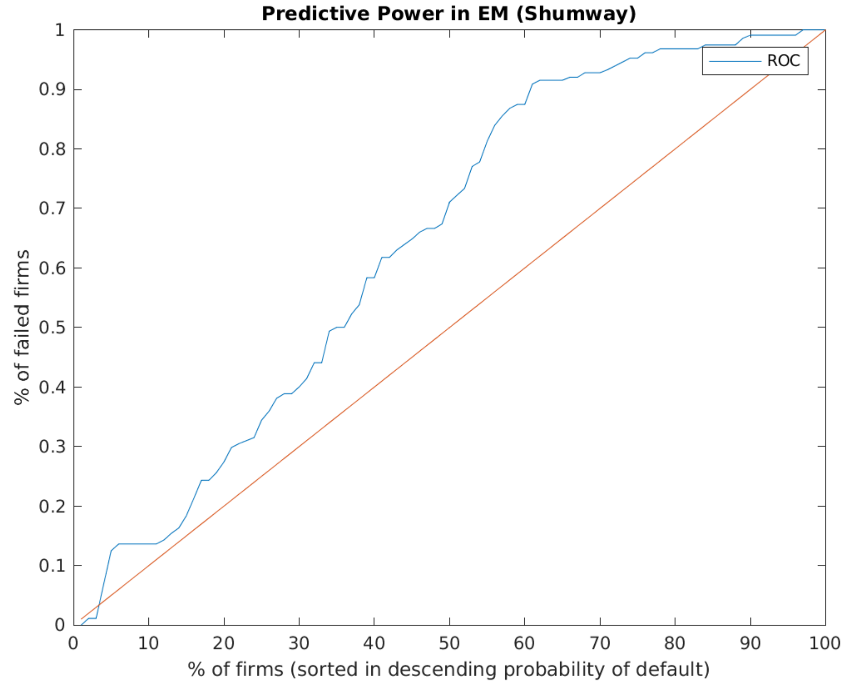


Figure 7: Shumway's variables on EM data

4.1 Prior models

Figures 7 and 8 use the Receiver Operating Characteristics to show the predictive power of Shumway's (2001) and Campbell et al.'s (2008) U.S.-based models when applied to my EM sample. For comparison purposes, Figures 9 and 10 report the predictive power of the same specifications when applied to my U.S. sample. Recall that a larger area under the ROC curve means better forecasting power, since the model correctly places more firms from the Default group in the most distressed deciles. When applying their models to my set of Emerging Market firms, we are able to determine with much less accuracy the probability that a firm will default in the next month.

4.2 Variable Selection

The poor performance of existing models on EM data calls for an emerging market-specific bankruptcy prediction model. Given the lack of emerging market-based evidence on this topic, there is not a well-defined benchmark specification to inform my variable selection. To overcome this shortcoming, I add the least absolute shrinkage and selection operator (LASSO) routine to my estimation. This will allow me to select, from a large set of explanatory variables, the subset with highest predictive power. The LASSO constrains the sum of the absolute value of the coefficients during the estimation process (maximum likelihood in our case), forcing some coefficients to equal zero. The result is enhanced prediction accuracy and interpretability of the coefficients. Tian, Yu, and Guo (2015) already employ this routine on U.S. data and achieve higher in- and out-of-sample predictability than Campbell et al.

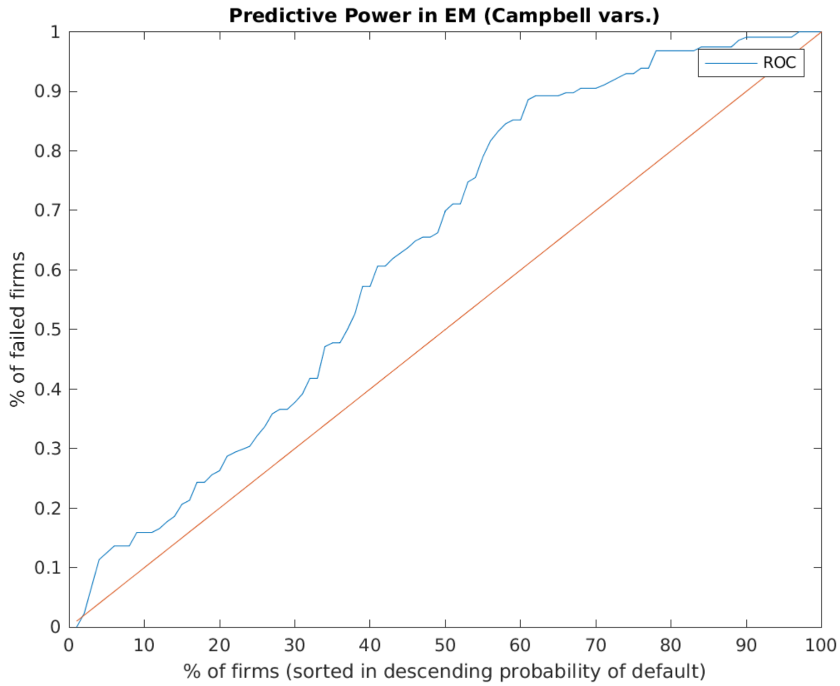


Figure 8: Campbell et al.'s variables on EM data

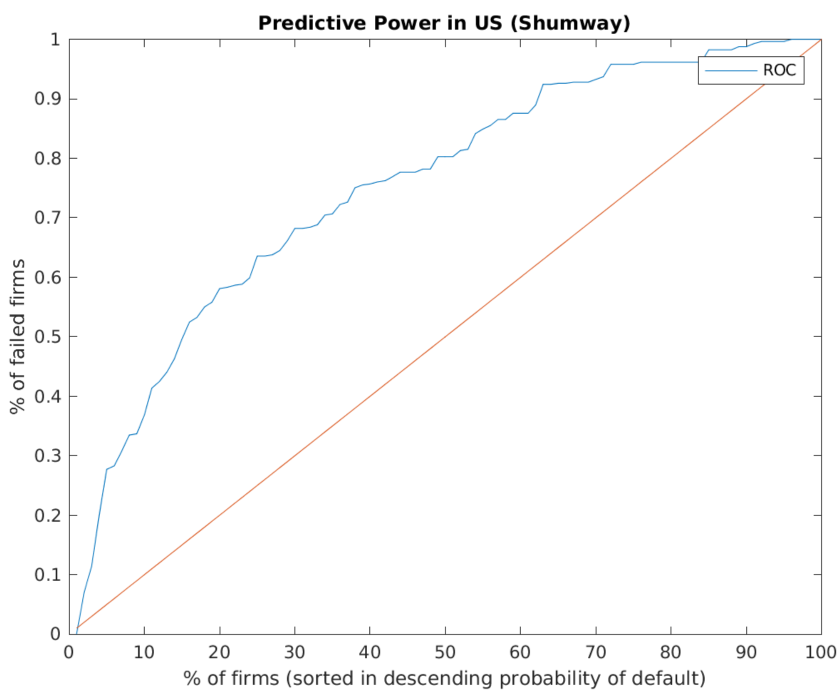


Figure 9: Shumway's variables on US data

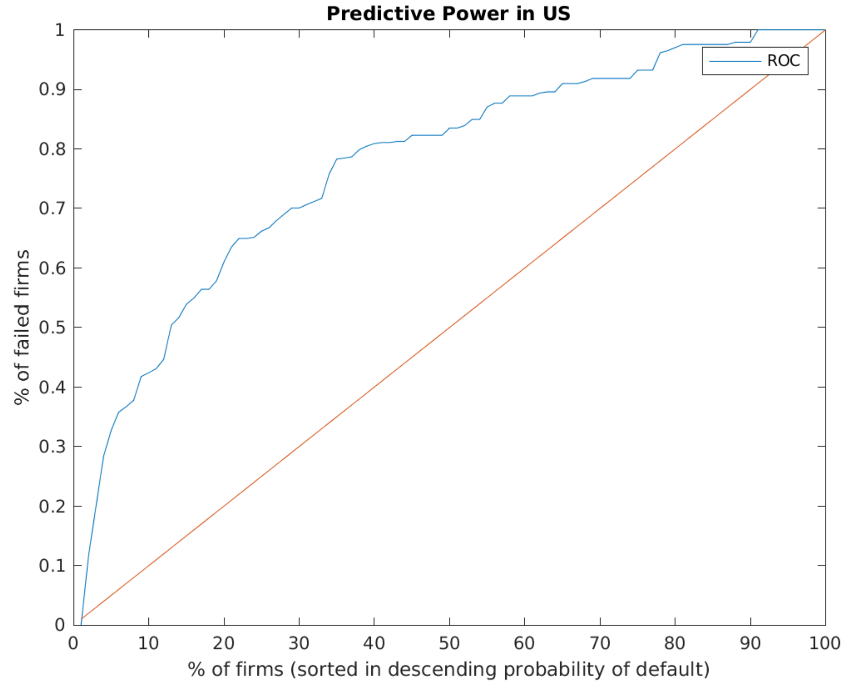


Figure 10: Campbell et al.'s variables on US data

(2008). Starting from theoretical arguments and existing advanced-economy specifications, the LASSO routine allows me to add statistical rigor to the variable-selection part of this exercise.

A first attempt at this procedure selected the following subset of variables with their respective coefficient sign: Total Liabilities/Total Assets (+), Market Value of Equity / Book Value of Equity (-), EBIT / Total Assets (-), Unemployment Rate (+), and ICRG's Composite Risk Rating (+). Figure 11 shows the coefficient path the LASSO routine followed. EBIT/Total Assets and Unemployment Rate are the first variables to move away from zero as lambda decreases, with negative and positive coefficients respectively.

When I test this model's performance, I find that it achieves much higher predictive power than Shumway's or Campbell et al.'s models, as Figure 12 shows.

5 Moving forward

I have so far shown the intuitive differences between distressed and non-distressed firms in emerging markets, demonstrated the lack of predictive power of existing U.S.-based models, and taken some steps towards specifying an EM-specific measure of corporate default risk. Next, I need to figure out how to include country - and possibly industry - fixed effects into the LASSO routine, consider a non-parametric LASSO estimation (as in Freyberger, Neuhierl, and Weber 2017), extend the variable selection exercise to longer horizons to test whether the set of variables changes with time to default, and test the pricing of distressed stocks in emerging markets.

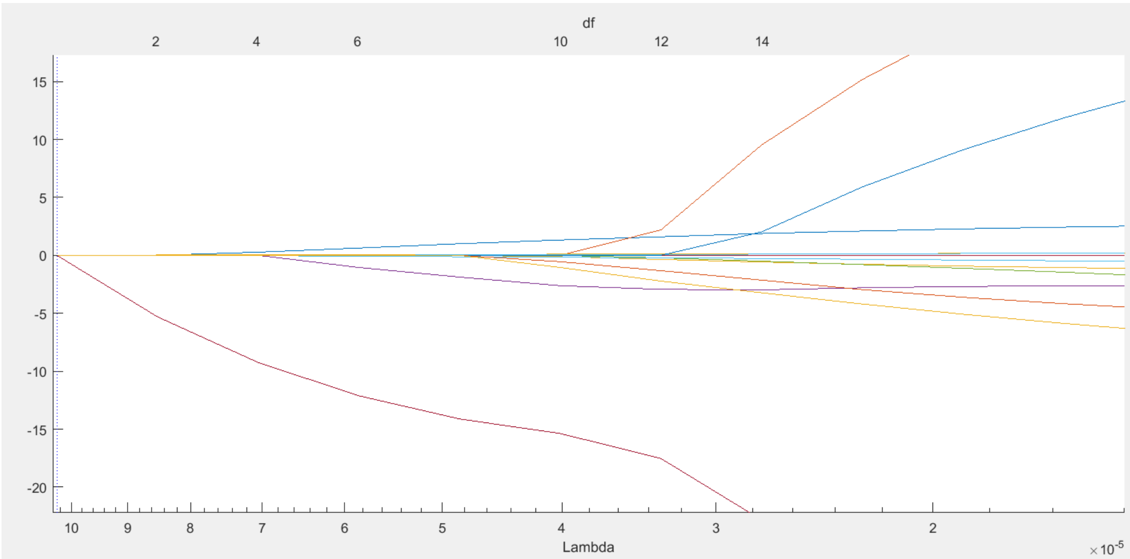


Figure 11: Coefficient path using LASSO variable selection on my set of explanatory variables

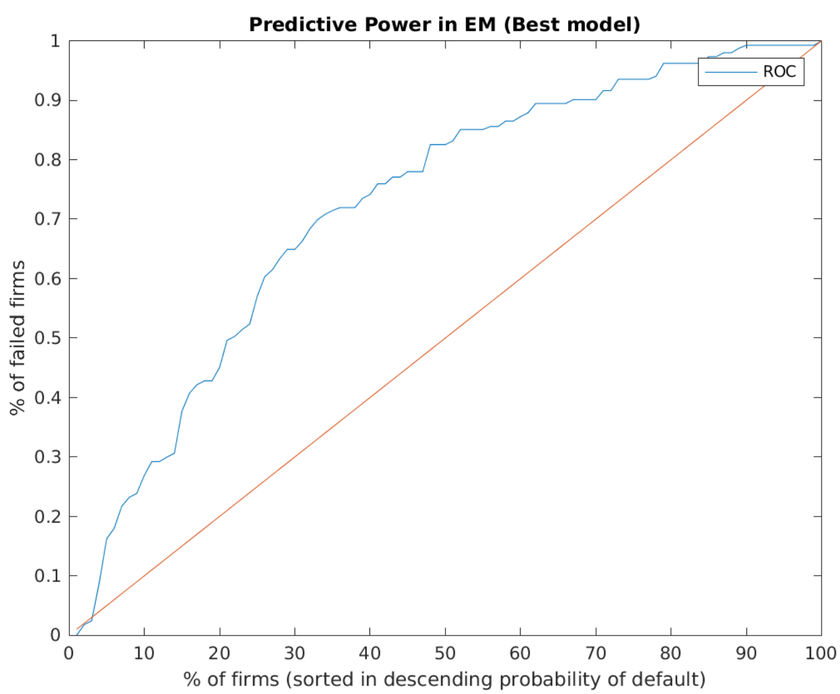


Figure 12: Forecasting performance of LASSO-selected model on EM data

For the asset pricing part, the objective is to determine whether investors are demanding the appropriate premium for bearing default risk. The default risk premium can be measured by placing stocks into quantiles (e.g. deciles) based on their probability of default as implied by my model. By treating each decile as a value-weighted portfolio, I can then calculate the average return (across years) of each portfolio in excess of the market. Campbell et al. (2008) perform an exercise of this kind and are surprised to find a negative risk premium associated with default risk. The average excess returns of their portfolios are in fact "strongly and almost monotonically declining in failure risk" - their safest and riskiest portfolios earned a 3.4% and -17% excess return per year, respectively. I wonder if Emerging Market stocks exhibit the same features.

References

Acharya, Viral, Stephen Cecchetti, José de Gregorio, Sebnem Kalemli-Ozcan, Philip Lane, and Ugo Panizza (2015) “Corporate Debt in Emerging Economies: A Threat to Financial Stability?”, September 2015, Brookings Institution Report.

Alfaro, Laura, Gonzalo Asis, Anusha Chari, and Ugo Panizza (2016): “Lessons Unlearned? Corporate Debt in Emerging Markets”, working paper, July.

Altman, E. (1968) "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," *Journal of Finance*, vol. 23 (September), pp. 589-609.

Altman, Edward (2005) “An Emerging Market Credit Scoring System for Corporate Bonds,” Emerging Market Review 6: 3011-323.

Arora, N., J. Bohn, and Z. Fanlin (2005) “Reduced form vs. structural models of credit risk: A case study of three models,” *Journal of Investment Management* 3 (4), 43–67

Avdjiev S., Chui M., Shin H. S. (2014) “Non-financial corporations from emerging market economies and capital flows”, *BIS Quarterly Review*, December 2014, 67–77.

Bank of Korea (2014) Financial Stability Report, April.

Bauer, Julian and Vineet Agarwal (2014) “Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test,” *Journal of Banking and Finance*, vol. 40, 432–442.

Beaver, William H. (1966) “Financial ratios as predictors of failure,” *Journal of Accounting Research*, 71–111.

Begley, Joy, Jin Ming, and Susan Watts (1996) "Bankruptcy classification errors in the 1980s: an empirical analysis of Altman's and Ohlson's models," *Review of Accounting Studies* 1, 267-284.

Ben S. Bernanke & John Y. Campbell (1988) "Is There a Corporate Debt Crisis?" *Brookings Papers on Economic Activity*, Economic Studies Program, The Brookings Institution, vol. 19(1), pages 83-140.

Bernanke, Ben and Mark Gertler (1989) “Agency Costs, Net Worth, and Business Fluctuations,” *American Economic Review*, Vol. 79, pp. 14-31.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1999) “The Financial Accelerator in and Quantitative Business Cycle Framework.” In: *Handbook of Macroeconomics*, Vol. 1C, ed. by John Taylor and Michael Woodford (Amsterdam: North-Holland), pp. 1531-1614.

Bharath, Sreedhar and Tyler Shumway (2008) “Forecasting default with the Merton distance to default model,” *Review of Financial Studies* 21 (3), 1339–1369.

Bruno, Valentina and Hyun Song Shin, (2015) “Global Dollar Credit and Carry Trades: A Firm-Level Analysis”, BIS Working Paper, No 510, August.

Caballero, Julian, Ugo Panizza, and Andrew Powell (2015) "The second wave of global liquidity: Why are firms acting like financial intermediaries?" IHEID Working Papers 21-2015, Economics Section, The Graduate Institute of International Studies.

Campbell, John, Jens Hilscher, and Jan Szilagyi (2008) “In Search of Distress Risk,” *Journal of Finance* 63, no. 6: 2899-2939.

Chava, Sudheer and Robert Jarrow (2004) “Bankruptcy prediction with industry effects,” *Review of Finance* 8, 537–569.

Chui, M, I Fender and V Sushko (2014) “Risks related to EME corporate balance sheets: the role of leverage and currency mismatch” *BIS Quarterly Review*, September, pp 35–47.

Crosbie, Peter, and Jeff Bohn (2003) “Modeling Default Risk,” Moody’s KMV White Paper, (San Francisco: Moody’s Investor Service) December 18.

Dell'Ariccia, Giovanni, Luc Laeven, and Robert Marquez (2015) *Financial Frictions, Foreign Currency Borrowing, and Systemic Risk*, Working Paper.

Domanski, Dietrich, Jonathan Kearns, Marco Jacopo Lombardi, and Hyun Song Shin (2015) “Oil and Debt”, *BIS Quarterly Review* (March): 55-65.

Friedman, Benjamin M. 1986. “Increasing Indebtedness and Financial Stability in the United States.” *Debt, Financial Stability and Public Policy*. Federal Reserve Bank of Kansas City.

Gabaix, Xavier (2011) “The Granular Origins of Aggregate Fluctuations,” *Econometrica* 79, 733–72.

Giesecke, Kay, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev (2011) “Corporate Default Risk: A 150-Year Perspective”, *Journal of Financial Economics* 102, 233-250.

Giesecke, Kay, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev (2014) “Macroeconomic effects of corporate default crises: a long-term perspective” *Journal of Financial Economics* 111, 297–310

Harvey, Campbell and Andrew Roper (1999) “The Asian bet” In: *The crisis in emerging financial markets*, ed. by Harwood, A., Litan, R.E., Pomerleano, M., Brookings Institution Press, Washington, DC, 29-115.

Hattori, Masazumi, Hyun Song Shin, and Wataru Takahashi (2009) “A Financial System Perspective on Japan’s Experience in the Late 1980s”, Technical report, Institute for Monetary and Economic Studies, Bank of Japan.

Hernandez Tinoco, M. and N. Wilson (2013) “Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables,” *International Review of Financial Analysis* 30, 394–419.

Hillegeist, S., E. Keating, D. Cram, and K. Lundstedt (2004) “Assessing the probability of bankruptcy,” *Review of Accounting Studies* 9, 5–34.

Houghton, Keith and David Woodliff (1987). “Financial Ratios: The Prediction of Corporate Success and Failure,” *Journal of Business Finance & Accounting* 14, 537-554.

IMF (2015) “Corporate Leverage in Emerging Markets—A Concern?” *Vulnerabilities, Legacies, and Policy Challenges Risks Rotating to Emerging Markets, Global Financial Stability Report*.

Kalemli-Özcan, Sebnem, Herman Kamil and Carolina Villegas-Sanchez (2015) “What Hinders Investment in the Aftermath of Financial Crises: Insolvent Firms or Illiquid Banks?” *Review of Economics and Statistics*, forthcoming.

Kaufman, Henry. 1986 “Debt: The Threat to Economic and Financial Stability”, *Debt, Financial Stability and Public Policy*. Federal Reserve Bank of Kansas City, pp. 15-26.

Kealhofer, Stephen (2003) “Quantifying Credit Risk I: Default Prediction,” *Financial Analysts Journal*, 59(1), 30-44.

Kealhofer, Stephen (2003) “Quantifying Credit Risk II: Debt Valuation,” *Financial Analysts Journal*, 59(3), 78-92.

Koepke, Robin (2015) “What Drives Capital Flows to Emerging Markets: A Survey of the Empirical Literature,” IIF Working Paper, Washington, April.

Kordlar, Ali and Nader Nikbakht (2011) "Comparing Bankruptcy Prediction Models in Iran,” *Business Intelligence Journal*, vol. 4, no. 2, 335-342.

Kraus, Allan and Robert Litzenberger (1973) “A state preference model of optimal financial leverage,” *Journal of Finance*, September.

Lanau, Sergi (2011) “Domestic Financial Regulation and External Borrowing,” Bank of England Working Paper No. 429.

Mendoza (2005) “Real Exchange Volatility and the Price of Nontradables in Sudden-Stop Prone Economies”, *Economia*, Fall, pp.103-148.

Mendoza, Enrique, and Marco Terrones (2008) "An Anatomy of Credit Booms: Evidence from Macro Aggregates and Micro Data." IMF Working Paper.

Merton, Robert (1974) “On the pricing of corporate debt: The risk structure of interest rates,” *Journal of Finance* 29, 449-470.

Modigliani, Franco, and Merton H. Miller (1958) "The Cost of Capital, Corporation Finance, and the Theory of Investment." *American Economic Review* 48 (June): 261-97.

Myers, Stuart, and Nicholas Majluf (1984) “Corporate financing and investment decisions when firms have information that investors do not have,” *Journal of Financial Economics* 13, 187–221.

Nobuhiro Kiyotaki and John Moore (1997) "Credit Cycles", *Journal of Political Economy* 105, no. 2 (April): 211-248.

Ohlson, James (1980) "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research* 19 (Spring): 109-31.

Opler, Tim C., and Sheridan Titman (1994) "Financial Distress and Corporate Performance," *The Journal of Finance* 49.3: 1015-040.

Pomerlano, Michael (1998) “The East Asian Crisis and Corporate Finances: The Untold Microeconomic Story,” *Emerging Markets Quarterly*, Winter: 14-27.

Powell, Andrew (2014) “Global Recovery and Monetary Normalization: Escaping a Chronicle Foretold?” Latin American and Caribbean Macroeconomic Report, Inter-American Development Bank.

Queen, Maggie and Richard Roll (1987) “Firm mortality: Using market indicators to predict survival,” *Financial Analysts Journal*, May-June, 9-26

Ramos, Manuel, Garcia, Santiago (2015) “Is trouble brewing for EMEs?” Bank of Mexico Working Paper, August.

Schularick, Moritz and Alan M. Taylor (2012) “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008,” *American Economic Review* 102 (2): 1029–61.

Shin, H S and L Zhao (2013) “Firms as surrogate intermediaries: evidence from emerging economies”, working paper, December 2013.

Shin, Hyun Song (2013) “The Second Phase of Global Liquidity and Its Impact on Emerging Economies” *Proceedings of the Asia Economic Policy Conference,* Federal Reserve Bank of San Francisco.

Shuetrim, Geoffrey, Philip Lowe, and Steve Morling (1993) “The Determinants of Corporate Leverage: A Panel Data Analysis,” Reserve Bank of Australia Working Paper No. 9313.

Shumway, Tyler (2001) ‘‘Forecasting Bankruptcy More Accurately: A Simple Hazard Model,’’ *Journal of Business* 74:1, 101–124.

Sobehart, Jorge and Sean Keenan (2001) “Measuring default accurately,” RISK 14, 31–33

Tian, S., Yu, Y., Guo, H., (2015). Variable selection and corporate bankruptcy forecasts. Journal of Banking & Finance 52, 89-100

Vasicek, Oldrich A. (1984) "Credit Valuation," Unpublished paper, KMV Corporation.

Vassalou, M., and Y. Xing (2004) “Default-Risk in Equity Returns,” *Journal of Finance,* 59:831-68.

Wu, Y., C. Gaunt, and S. Gray (2010) “A comparison of alternative bankruptcy prediction models,” *Journal of Contemporary Accounting and Economics,* vol. 6, p. 34–45

Xu, Ming and Chu Zhang (2009) “Bankruptcy Prediction: The Case of Japanese Listed Companies,” *The Journal of Review of Accounting Studies* 14: 534-558

Zmijewski, Mark (1984) ‘‘Methodological Issues Related to the Estimation of Financial Distress Prediction Models,’’ *Journal of Accounting Research Supplement,* 59–86.