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Bottom-Up Default Analysis of Corporate Solvency Risk: An Application to Latin America

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I N T E R N A T I O N A L M O N E T A R Y F U N D

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Abstract

This paper suggests a novel approach to assess corporate sector solvency risk. The approach uses a Bottom-Up Default Analysis that projects probabilities of default of individual firms conditional on macroeconomic conditions and financial risk factors. This allows a direct macro-financial link to assessing corporate performance and facilitates what-if scenarios. When extended with credit portfolio techniques, the approach can also assess the aggregate impact of changes in firm solvency risk on creditor banks' capital buffers under different macroeconomic scenarios. As an illustration, we apply this approach to the corporate sector of the five largest economies in Latin America.

JEL Classification Numbers: F4, G21, G31

Keywords: Macro-financial, default risk, corporate sector, bank capital, forward intensity models, economic scenarios, simulation

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I. Introduction

A comprehensive assessment of corporate sector vulnerabilities requires identifying complex macro-financial dynamics that influence the behavior and performance of individual firms. This paper proposes a specialized method to capture macro-financial linkages in order to more accurately predict the solvency risk of individual firms.

Since the devastating financial crisis in 2008, much effort has been expended to develop new analytical tools that can better reflect the nonlinear outcomes of macro-financial interactions. Witness, for instance, the burgeoning work on systemic risk analytics (Bisias et al, 2012); its rapid integration in macro-financial frameworks (Gauthier and Souissi, 2012), and the incorporation of macro-financial linkages in supervisory stress tests conducted by central banks and supervisory agencies (Siddique and Hasar, 2013).

This paper develops a new tool using the novel bottom-up default analysis (BuDA) introduced by Duan, Miao, and Chan-Lau (2015). Further information and data can be downloaded from the link below.[2] The model captures the dynamic interplay between the real economy and the financial sector to provide probabilistic assessments of changes in corporate solvency risk under different macroeconomic scenarios. To further link the corprorate and financial sector, the BuDA analysis is extended with the portfolio credit risk model of Vacisek (1987, 2002) to estimate how changes in corporate solvency risk would affect the amount of loan provisions and capital that the banking system would need to set aside against its corporate exposure.

To illustrate the model, we apply it to five large economies in Latin America (Brazil, Chile, Colombia, Mexico, and Peru—henceforth LA-5) at end-April 2016, when concerns about corporate leverage in Latin America reached a peak (IMF, 2016b).

The remainder of the paper is structured as follows. Section II lays the groundwork for the corporate solvency risk analysis with an overview of recent corporate debt developments in the LA-5 countries. Section III introduces the BuDA methodology. Section IV illustrates its application to the LA-5 countries. Section V concludes.

II. Recent Corporate Debt Developments: LA-5 Countries

A. Financial Ratio Analysis

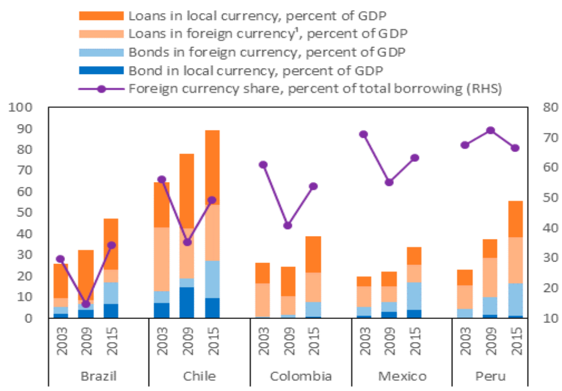
Aggressive monetary policy accommodation since the 2008 financial crisis has kept interest rates low around the world. Firms in many emerging market economies, including in Latin America, have taken advantage of the low cost of borrowing to increase their debt to finance their business operations. The average corporate debt among the LA-5 countries rose by about 14 percent of GDP between 2009 and 2015, double the 7 percent rate observed over the pre-crisis period of 2003– 2009 (Figure 1). A significant share of the corporate debt is bank loans. In Brazil and Mexico, the banking system has roughly 22 percent of its total assets in corporate loans, while in Peru the share is as high as 45 percent of banking system

[2] http://rmicri.org/en/client_login/?next=/en/data/companyalldata/

(continued…)

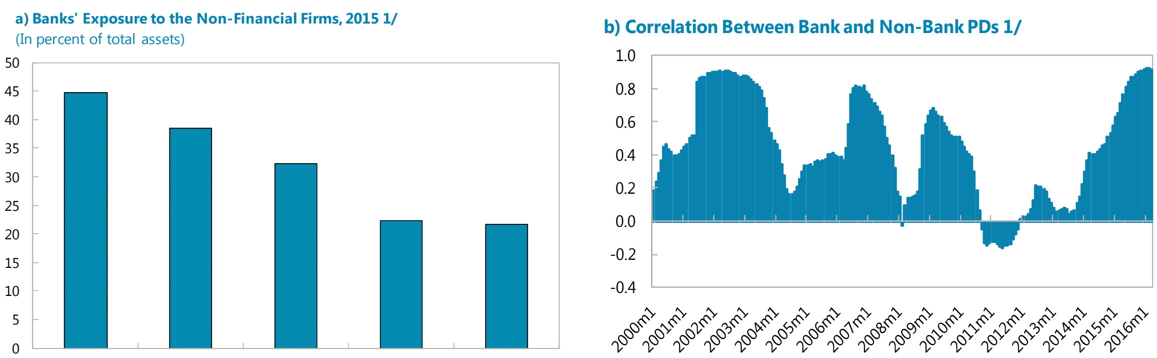
total assets (Figure 2, left panel). As a result, the banking and corporate sectors in these countries are closely intertwined, as reflected in the high correlation between market estimates of the solvency risk of the bank and corporate sector; during episodes of economic distress the correlation rises to close to 0.9 (Figure 2, right panel).[3] Corporate bond issuance has also increased markedly since 2010, but from lower levels. Both Colombia and Peru saw a sharp rise in the issuance of foreign currency denominated bonds.

Figure 1. Bond and Loan Debt by Non-Financial Corporates



Sources: BIS, External Debt Statistics and Securities Statistics; Dealogic; national authorities; and IMF staff calculations.
¹ Includes foreign currency lending by domestic institutions and lending by foreign institutions to the non-bank private sector.

Figure 2. LA5: Banks and Non-Financial Corporate Sector



Sources: BIS, Dealogic, IMF, and authors' calculations.
1/Includes loans, securities, shares, financial derivatives, trade credits, and settlement access except for Peru, which includes only loans and securities, due to data limitations.

1/Rolling 24 month correlation between probabilities of defalt in the bank and non-bank sectors for each country.

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[3] Sectoral PD series used in the calculation were obtained from the database maintained by the Credit Research Initiative, Risk

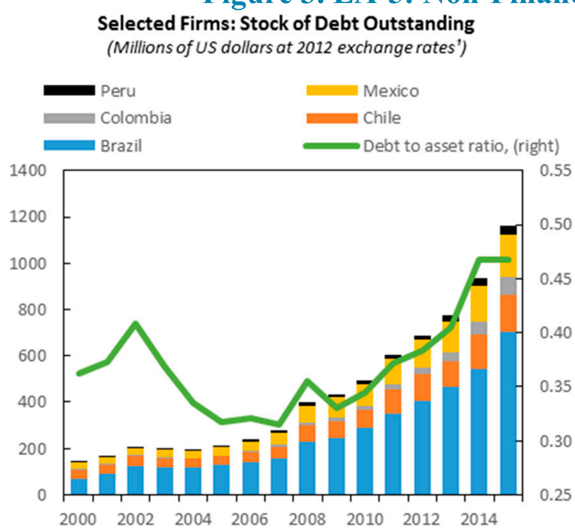
Management Institute, National University of Singapore. The database is freely available at rmicri.org upon registration.

(continued…)

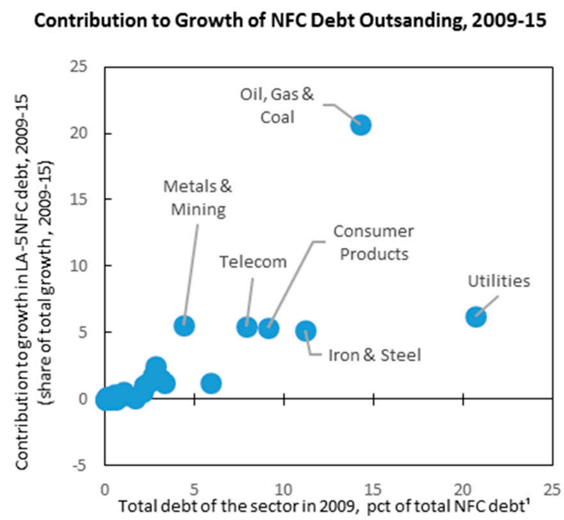
For a closer look at the financial health of the corporate sector, we constructed a sample of 1121 publicly traded non-financial firms located in the LA5 countries from Bloomberg LLC. This sample is used in the BuDA exercise which we discuss later.

In the post-crisis period of 2009 – 2015, the total stock of debt[4] for the firms in the sample, measured in constant dollar terms rose by 167 percent (Figure 3, left panel). Similarly, weighting the debt of each firm by the total debt to reflect relative size, shows the debt-to-asset ratio rising to 47 percent from 33 percent, a 14 percentage point increase. Firms in Brazil recorded the largest increase, 185 percent, followed by those in Chile, 120 percent, and Mexico, 108 percent.

Figure 3. LA-5: Non-Financial Corporate Debt, 2000–15



Sources: Bloomberg, LLP; and IMF staff calculations.
[1] Total debt reported by firms in local currency converted to US dollars at fixed 2012 exchange rates to convey the proportional increase in debt burden and relative size of debt by country.
[2] Average debt to asset ratio weighted by the firms total debt outstanding at fixed 2012 exchange rates.



In addition, firms in the most indebted industrial sectors as of 2009 contributed the most to the increase in non-financial corporate debt observed by end-2015 (Figure 3, right panel). Among these sectors, five were responsible for almost half of the increase in indebtedness: oil, gas, and coal accounted for 21 percent; utilities added another 6¼ percent, metals and mining, telecommunications, and consumer products, about 5½ percent each.

[4] Most firms report financial statements in local currency with foreign currency denominated debt adjusted for changes in exchange rates. To sum the stock of debt across currencies without introducing the additional impact of foreign exchange fluctuations, nominal debt stocks in local currency are converted to US dollars at fixed 2012 exchange rates. With this adjustment, the analysis focuses on the change in the debt stock (debt burden) and not on the levels.

Table 1 reports estimates for six different indicators of corporate debt sustainability, including the debt-to-asset ratio, the effective interest rate, the short-term liability ratio, return on assets, revenue growth, and the cash-to-debt ratio as of end-2007 and end-2015. Higher values for the first three indicators signal higher risk while lower values for the latter three signal lower risk. It is important to look at these indicators to assess the ability of firms to generate revenue, and hence their repayment capacity and their resilience to shocks.

The empirical distribution of the indicators can be divided in two halves: the weak tail, comprising firms with risk above the median, and the strong tail, comprising firms with risk below or equal to the median.

Within the weak tail, we can distinguish three other subcategories: the extreme tail, comprising firms in the top 20th risk percentile range; the moderate tail, comprising firms in the next 15th risk percentile range; and the low tail, comprising the next 15th risk percentile range. For each of these subcategories, Table 1 reports the median value of the indicator and the cumulative share of debt in percent of total assets. For comparison purposes, we also report the corresponding figures for the strong tail.

Among the indicators, the deterioration of the debt-to-asset ratio, or the increase in leverage, from 2007 to 2015 stood out. For the weakest cohort of firms, those in the extreme weak tail, the median value rose to 52 percent from 44 percent. While this cohort only comprises one out of five firms in the sample, in 2015 it accounted for 60 percent of the total debt in the non-financial corporate sector, up from 40 percent in 2007. Risks appeared concentrated in the commodities and telecommunication/media subsectors, and to a lesser extent in the construction and utilities subsector.

Another source of concern was the decline in profitability, as measured by the return on assets, experienced during the 2007–15 period. Unsurprisingly, the least profitable firms were also the most indebted ones. Within the extreme weak tail, there has been an eight-fold increase in their share of total debt, which stood at 42 percent at end-2015.

The trend partly reflected the effects of the boom-bust commodity cycle. In 2007, 77 percent of the debt of firms in the commodity subsector was in the strong tail category. By 2015, about the same share of debt had shifted to the worst performing weak tail. The construction subsector experienced a similar migration from the strong tail (74 percent of the subsector total debt in 2007) to the weak tail (70 percent) in 2015. Notably, the decline in profitability came hand in hand with a decline in revenue growth, impairing the cash flow available to service interest and amortization expenses. The decline was most acute in the construction and utilities subsectors.

The share of assets held in cash and short term investment, a liquidity measure, captures a firm’s ability to use liquid assets to meet debt service obligations. Relative to 2007, cash ratios improved marginally, with the cumulative share of debt held by the extreme and moderately cash strapped firms down to 34 percent in 2015, 2 percentage points below its 2007 value. Again, the bust of the commodity super-cycle is evident, with the commodity subsector recording the sharpest drops in cash ratios. The debt concentration in the subsector, however, migrated towards both the low weak tail and strong tail, offsetting somewhat the weaker cash position of the firms.

Table 1. Sustainability of Corporate Debt in the LA-5: Weak Tail Analysis

	Median value of indicator by percentile segment[1]				Share of total debt of firms in sector and indicator group				Total debt of firms in sector Sector (mil USD)[2]
	Extreme: 20th pctl. pctl.	Moderate: 15 pctl range	Low: 15 pctl range	Strong tail	Extreme: 20th pctl. pctl.	Moderate: 15 pctl range	Low: 15 pctl range	Strong tail	
All Non-financial corporates									
Debt to asset ratio, 2015	**0.52**	0.38	0.31	0.11	**60.6**	12.6	18.1	8.8	1,159.1
Debt to asset ratio, 2007	**0.44**	0.31	0.24	0.08	**39.6**	20.6	17.9	21.9	279.7
Effective interest rate[3] (percent), 2015	23.80	11.75	8.59	4.64	5.7	11.0	9.1	74.2	1,140.2
Effective interest rate[3] (percent), 2007	32.04	13.34	10.36	6.18	6.5	9.4	25.8	58.3	227.8
Short-term liability ratio[4], 2015	0.85	0.64	0.50	0.29	2.9	4.5	4.0	88.6	1,159.8
Short-term liability ratio[4], 2007	0.91	0.72	0.60	0.36	2.1	5.3	8.1	84.5	279.1
Return on assets (percent), 2015	**-9.36**	-0.73	1.51	5.45	**42.0**	13.9	11.2	32.9	1,160.7
Return on assets (percent), 2007	**-6.22**	1.42	3.78	9.97	**5.1**	17.3	12.6	65.0	276.2
Annual growth rate of sales (pct), 2015	**-21.07**	**-3.16**	4.18	16.07	**14.8**	34.3	15.8	35.2	1,159.7
Annual growth rate of sales (pct), 2007	**-11.32**	**3.34**	9.08	25.19	**7.0**	11.7	26.2	55.1	276.1
Cash to debt ratio, 2015	0.03	0.11	0.19	0.56	8.2	25.6	32.4	33.9	1,160.8
Cash to debt ratio, 2007	0.02	0.09	0.20	0.73	20.9	15.5	16.0	47.6	279.6
Memorandum: Selected Indicators by Sector									
Commodity producers: energy, metals, and mining									
Debt to asset ratio, 2015	**0.52**	0.39	0.33	0.15	**72.8**	6.8	16.8	3.5	493.4
Debt to asset ratio, 2007	**0.38**	0.27	0.21	0.03	**34.2**	31.0	31.9	3.0	73.4
Return on assets (percent), 2015	**-14.06**	**-3.72**	0.01	2.84	**15.9**	**60.4**	11.0	12.7	497.8
Return on assets (percent), 2007	**-2.98**	**2.64**	7.45	17.63	**2.1**	**3.4**	17.4	77.2	73.2
Annual growth rate of sales (pct), 2015	**-25.13**	-13.25	-5.69	10.28	**10.7**	12.6	4.5	72.2	497.4
Annual growth rate of sales (pct), 2007	**-14.32**	5.58	10.69	33.08	**1.9**	2.6	32.6	62.9	73.1
Cash to debt ratio, 2015	0.02	**0.12**	**0.19**	**0.39**	2.8	**30.0**	**49.9**	**17.3**	497.8
Cash to debt ratio, 2007	0.07	**0.21**	**0.43**	**1.76**	25.9	**17.9**	**21.0**	**35.2**	73.5
Utilities									
Debt to asset, 2015	**0.49**	0.38	0.31	0.14	**31.7**	23.6	25.8	18.9	160.0
Debt to asset, 2007	**0.45**	0.35	0.30	0.10	**17.9**	32.1	18.8	31.1	73.4
Annual growth rate of sales (pct), 2015	**-13.10**	**3.29**	8.13	18.80	**12.9**	**17.0**	22.62	47.51	162.23
Annual growth rate of sales (pct), 2007	**-8.76**	**0.65**	2.91	18.67	**8.4**	**6.2**	19.76	65.67	71.29
Consumer/Retail									
Debt to asset, 2015	**0.50**	0.36	0.30	0.09	**47.6**	13.9	20.1	18.4	159.5
Debt to asset, 2007	**0.43**	0.31	0.24	0.09	**38.8**	24.9	20.0	16.4	38.9
Return on assets (pct), 2015	**-4.76**	0.09	2.22	6.02	**14.4**	8.0	18.7	58.9	159.6
Return on assets (pct), 2007	**-1.69**	2.05	4.00	9.07	**7.3**	18.3	10.9	63.5	38.3
Telecommunications & Media									
Debt to asset, 2015	**0.53**	0.37	0.22	0.07	**80.4**	9.6	3.8	6.1	108.0
Debt to asset, 2007	**0.39**	0.30	0.26	0.12	**11.7**	38.9	23.0	26.4	21.6
Effective interest rate[3] (percent), 2015	20.93	**10.31**	8.46	4.83	0.7	**29.0**	1.6	68.8	104.9
Effective interest rate[3] (percent), 2007	18.86	**11.38**	10.32	7.27	13.2	**4.0**	12.0	70.8	19.4
Return on assets (pct), 2015	**-7.62**	-2.72	-0.04	4.47	**29.1**	1.0	3.2	66.7	109.1
Return on assets (pct), 2007	**-0.56**	1.75	4.29	9.47	**12.1**	7.1	14.1	66.7	21.6
Construction									
Debt to asset, 2015	**0.62**	**0.39**	**0.33**	0.18	**61.9**	**11.1**	**18.9**	8.1	80.2
Debt to asset, 2007	**0.40**	**0.31**	**0.24**	0.09	**74.1**	**8.3**	**4.6**	13.0	28.5
Return on assets (pct), 2015	**-3.57**	**0.93**	2.08	4.49	**50.5**	**20.0**	5.9	23.6	81.6
Return on assets (pct), 2007	**-1.60**	**1.56**	3.75	9.38	**3.6**	**12.6**	9.2	74.5	28.1
Annual growth rate of sales (pct), 2015	**-22.52**	**-1.76**	2.54	19.92	**11.5**	**18.4**	2.6	67.5	81.6
Annual growth rate of sales (pct), 2007	**-29.14**	**-1.62**	7.25	18.49	**1.9**	**4.2**	12.9	80.9	28.1

Sources: Bloomberg, LLP and IMF staff calcualtions.

[1] After screening for outliers 5 standard deviations above and below the annual mean across all finanical and non-financial firms in the sample, firms in the "weak" tail (high values for debt to asset, effective interest rate, and short term debt ratio and low values for return on assets, growth rates of sales, and cash to debt ratio) were grouped by their percentiles within each indicator. Percentile ranges are as follows: the extreme concern include the 0-99th/1-20th percentiles; moderate concern, 65-79/21-35th, and low conern 50-64/35-50th. The strong tails (50-99 and 0-50th percentiles) are included for comparison.

[2] Total debt in US dollars converted at constant 2012 exchange rates. Sums of debt for different indicators of the same year vary on accont of missing observations for the indicator.

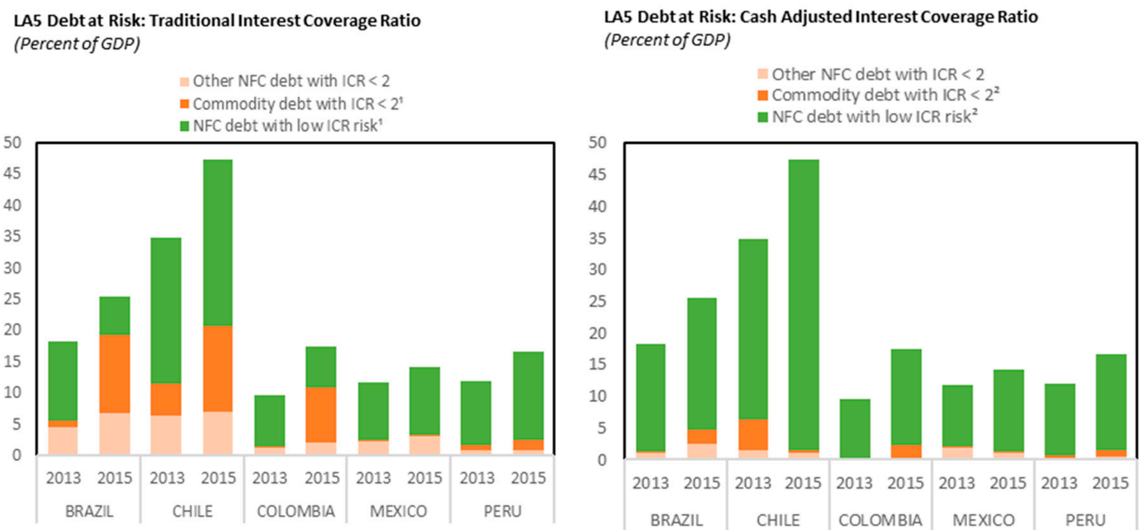
[3] Effective interest rate calculated as interest expense in the current year in percent of the average of total debt outstanding in the currrent and previous year.

[4] Liabilities and the current poriton of long debt coming due within 12 months in percent of total liabilties.

B. Debt-at-Risk

In addition to the six corporate debt sustainability measures analyzed above, it is also useful to examine the ability of firms to use their earnings stream to meet the interest payments on their debt. Given a fixed period of time, we can measure this liquidity buffer using the interest coverage ratio, or the ratio of earnings before income and taxes to the amount of interest the firm has to pay on its debt. Following IMF (2014), the debt of firms with an interest coverage ratio lower than two is denoted as *debt-at-risk*[5]. Figure 4 shows the debt at risk in each of the LA5 countries in 2013 and 2015.

Figure 4. Debt at Risk



Source: Bloomberg, LLP and IMF staff calculations.
[1] Stock of debt owed by firms with interest expense to EBIT ratios (ICR) less than 2.
[2] Stock of debt owed by firms with interest expense plus stock of cash to EBIT ratios (ICR) less than 2.

In all countries, debt-at-risk increased during the two-year period, especially in Brazil, Colombia, and Chile (left panel). However, the position looks better when cash on hand plus earnings is used to meet interest expenses. As noted above, firms in the LA-5 countries increased their holdings of cash and liquid assets. Allowing for the use of cash and liquid assets, firms had enough liquid buffers to keep debt-at-risk low. In fact, debt-at-risk in Chile actually declined under this estimate. Hence, despite the increase in debt, LA5 firms had accumulated sufficient cash buffers, improving their resilience to shocks.

[5] The threshold value of 2 is a commonly used benchmark in the literature.

III. The Bottom-Up Default Analysis (BuDA) Methodology: an Overview[6]

The review of debt and liquidity indicators suggests that the corporate sector in the LA-5 countries has become more vulnerable to shocks due to higher debt levels and lower profitability, particularly in the commodities and construction sectors. Nevertheless, healthy cash buffers and longer debt maturities have mitigated the vulnerability from higher debt exposure, reducing debt-at-risk. This assessment is consistent with the evidence presented by Rodrigues Bastos et al. (2015) who found that during the 2010-14 bond issuance boom, the regional composition of new debt featured longer maturities, lower interest rates and a higher proportion of fixed rate terms.

Given this assessment, is the overall corporate solvency risk in LA-5 countries considered low or high, and how will it evolve as the macroeconomic outlook changes? It is clear that, while useful as a first approximation of emerging pressure points, financial ratios cannot provide a comprehensive view of corporate solvency risk. It is an accounting-based approach that is static and backward looking, and largely independent of the macroeconomic outlook.

The BuDA model attempts to more fully capture the complex macro-financial dynamics that drive corporate solvency risk. In this model, macroeconomic and financial conditions directly affects a firm's ability to honor its obligations, including the timely payment of interest and principal, or its probability of default (PD). Taking it a step further, the model links changes in PDs to their impact on creditor banks' provisioning and capital levels by drawing on Vacisek's (1987, 2002) credit risk portfolio model. This highlights the close nexus between the corporate and banking sectors, and facilitates what-if scenarios that are useful as a guide to policymakers.

Conceptually, the BuDA methodology can be understood as a four-step procedure, illustrated in Figure 5:

1. Specify a macroeconomic scenario.
2. Forecast economy-wide and firm specific risk factors under the specified macroeconomic scenario.
3. Use risk factors as inputs in a forward intensity model to yield the projected PDs of the firm.
4. Use projected PDs as inputs in the credit portfolio module to assess creditor banks' provisions and capital needs associated with the default risk of the firm.

We now turn to a discussion of the different blocks of the methodology (see annex for a more complete discussion).

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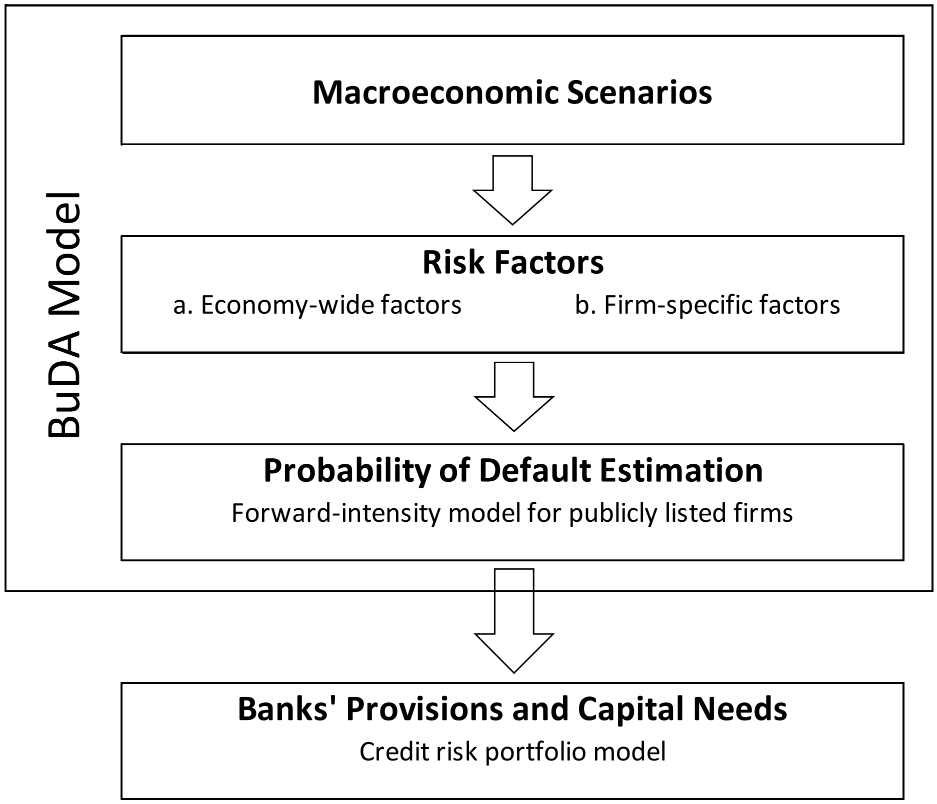
[6] The BuDA methodology was jointly developed by researchers at the Credit Research Initiative at the Risk Management Institute, National University of Singapore (RMI-CRI, NUS), and the International Monetary Fund (Duan, Miao and Chan-Lau, 2015. Recent examples of policy work using this methodology include IMF (2016b, Chapter 3), IMF (2016c, Chapter 2; 2016e, Chapter 2), and IMF (2016d) among others.

Figure 5. BuDA and Banks' Buffer Needs: Conceptual Approach



Macroeconomic Scenarios

The succesful application of BuDA hinges on the proper specification of the macroeconomic scenario. It should capture the economic conditions envisaged in the analysis and include the most relevant economic and financial variables. A typical analysis would consider several scenarios, including a baseline scenario and possible deviations from it. The alternative scenarios can be better or worse than the baseline scenario, depending on whether the analysis focuses on upside or downside risk (Ziemba, 2007). Not surprisingly, central banks, supervisory agencies, policy institutions, and risk managers tend to focus more on downside risk scenarios.

Risk Factors

Once the scenario is set, BuDA forecasts the behavior of the risk factors conditional on the economic and financial conditions in the scenario. The set of risk factors is predetermined in BuDA and includes both economy-wide factors, affecting all firms in the economy, and firm-specific factors, contributing to the idiosyncratic default risk of individual firm.

The ability to predict default guides the choice of risk factors. Results by Duan, Sun, and Wang (2012) narrow the set of risk factors to twelve variables with a high predictive accuracy, as measured by standard measures such as the area under the receiver operating characteristic (AUROC). For a one-year default prediction horizon, the AUROC of BuDA's PD forward intensity model is in the range of 85 percent to 91 percent (RMI-NUS, 2015). For comparison purposes, an uninformative model would have an AUROC of 50 percent, and a perfect model would have an AUROC of 100 percent. Table 2 lists these variables.

Table 2: Economy-Wide and Firm-Specific Risk Factors

Nature	Description	Level/Trend 1,2/
Economy-wide	Return of domestic stock market index	Current
	Short-term domestic interest rate	Current
Firm-specific	Financial statements-based factors	
	Liquidity (cash + short-term investments/total assets)	Trend and level
	Profitability (Net income/total assets)	Trend and level
	Market-based factors	
	Distance-to-default (volatility adjusted leverage)	Trend and Level
	Size (market capitalization relative to median market capitalization)	Trend and Level
	Market misvaluation (market cap + total liabilities/ total assets)	Current
	Idiosyncratic volatility	Current

1/ The level is computed as the 12-month average value of the factor.

2/ The trend is computed as the difference between the current value of the factor and its 12-month average

There are two economy-wide (or common) risk factors, the return of the domestic stock market index and a short-term domestic interest rate. Two of the firm-specific risk factors, liquidity and profitability, rely on financial statement data. The remaining firm-specific risk factors combine information from market prices and financial ratios.

Among the firm-specific factors, BuDA measures liquidity as the ratio of cash and short-term investments to total assets; and profitability as the ratio of net income to total assets. The measure of volatility-adjusted leverage is a variation of the distance-to-default (DTD), based on the Merton (1974) structural pricing model, and first proposed by Kealhofer, McQuown and Vasicek (KMV) as described in Crosbie and Bohn (2000), but correcting for the higher leverage financial firms exhibit relative to non-financial firms (Duan, Sun, and Wang, 2012). BuDA also takes into account the relative size of the firm since, in general, large firms are less likely to default. The relative size variable is defined as the natural logarithm of the ratio of the market capitalization of the firm to the median market capitalization of the firms in the economy[7]. Market mis-valuation is measured as the market-to-book asset ratio.[8] The idiosyncratic volatility of a firm is set equal to the standard deviation of the residuals obtained after regressing a firm's equity returns on the returns of the domestic market index[9].

[7] The median refers to the average median PD value of the sample of non-financial firms analyzed in each country. In the calculations, the average is calculated over 1000 simulations.

[8] The term mis-valuation, the term is used in a somewhat generic sense; in an efficient/steady state scenario, market and book value would be similar.

[9] The currency denomination mix in corporate debt is not considered separately in the BuDA framework. The model only looks at total debt, as incorporated into several of the firm-specific factors. The effects of currency mismatches on solvency risk is captured indirectly through market movements, via volatility and distance to default.

A brief description of the methodology to forecast risk factors is as follows:

a. For economy-wide risk factors. For each country, risk factors are obtained from a regression of the stock index and short-term interest rate on a set of macroeconomic variables.

b. For firm-specific risk factors. For each country, a two stage regression is estimated: (i) in the first stage, firm-specific risk factors such as profitability and liquidity are regressed on macroeconomic and financial variables to obtain the average risk factors for all firms in a given industrial group; 2) Once the average value is estimated, the second stage involves modeling the "distance" of individual firms to the industry average.[10]

Probability of Default Estimation

With the forecasted risk factors as inputs, it is straightforward to project the PDs of individual firms under the economic scenario using the Duan-Sun-Wang (DSW) forward intensity model (Duan, Sun, and Wang, 2012). In the BuDA implementation, the DSW model allows PDs to be projected for horizons ranging from one-month to five-years ahead. The PDs of individual firms can be aggregated to assess default risk economy-wide, in specific industrial sectors, or for ad-hoc groups of firms. The PDs can be decomposed into their key macroeconomic drivers as described in the annex.

Banks' Provisions and Capital Needs

Problems in the non-financial corporate sector could spill over to the domestic banking sector, among other creditors, if firms fail to repay their loans. Even if loans are repaid, banks need to hold provisions and capital buffers against potential higher losses in their loan portfolios. The projected PDs, when used as inputs in a standard credit portfolio model, provides estimates of creditor banks' provision and capital needs under the macroeconomic scenarios. Changes in the PDs of borrowers affect their ability to repay their loans, and therefore affects the loan portfolio loss distribution. The resulting changes to the loan portfolio's expected loss and tail-risk measures such as Value-at-Risk (VaR) thus require adjustments to the initial level of provisions and capital buffers held by the bank. This is common risk management practice in the banking system.

To analyze the linkages between solvency risk in the corporate sector and the banks' corporate loan portfolio, we assume that all banks in a country are homogeneous and hold an identical, granular, and stylized corporate loan portfolio. Each loan has the average PD and a loss given default of 40 percent. Details are provided in the annex.

We put the methodology to work in the next section.

[10] The potential noise from outliers (firms or industries) will be addressed to some extent by using median PDs in the methodology to compute provisions and capital needs.

IV. A BuDA Case Study: Adverse Commodity Shocks in LAC-5 Countries

To complement the earlier financial ratio analysis, we apply the BuDA analysis to the LA-5 countries. To put this in context, we use the regional baseline as presented in the IMF World and Regional Economic Outlook reports (IMF 2016a, and b)., where they noted that "continued vigilance in monitoring corporate balance sheets and asset quality of banks was [is] warranted given rising corporate leverage, modest growth prospects… Growth prospects over the next five years will likely remain subdued, particularly for those facing lower commodity prices and weak investment". In the following analysis, we shock the baseline with a commodity price decline, and examine the potential implications for the banking sector, the latter measured in terms of provisions and capital buffers needs.

A. Macroeconomic Scenario Design

Macroeconomic variables

As noted above, the innovation of the BuDA approach is in the mapping of macroeconomic scenarios to corporate solvency risk and how this, in turn, affects banks' capital and provisions. The judicious design of the macroeconomic scenario and variable selection is therefore important. For the LA-5 countries, various empirical studies (e.g. Cavallo and Valenzuela (2007) and IMF 2016) identify GDP growth, the US High Yield and 10-year US Treasury rate, commodity prices, and the US-dollar exchange rate as significant variables in predicting corporate bond spreads:

- External variables--commodity (oil and metal) prices, aggregate demand conditions in advanced economies and external borrowing cost.[11]
- Domestic variables--real GDP growth rate and the exchange rate vis-à-vis the U.S. dollar.

The starting point of the analyis is April 2016 with a projection period through end-2017.

Baseline scenario

As of April 2016, the baseline scenario assumed global demand would remain subdued, reflecting key transitions in the global economy related to the gradual slowdown and rebalancing in China, lower commodity prices, and tightened global financial conditions. Against this backdrop, economic activity in Latin America and the Caribbean was projected to decline by 0.5 percent in 2016, with many countries handling the transition in an orderly fashion and continuing to grow modestly. Overall, medium-term growth was likely to remain subdued; with commodity exporters in need to reallocate capital and labor out of resource-intensive sectors and other economies in need to replenish their capital stocks.

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[11] For the analysis, metal prices are proxied by the IMF's composite price index and the oil price is the simple average of three crude oil spot prices (APSP); aggregate demand of advanced economies is measured by the growth rate of a composite index of advanced economies' real GDP; external borrowing cost is measured by U.S. dollar short-term rates, (i.e. the U.S. Federal Fund rates), and U.S. dollar long-term rates, (i.e. the U.S. 10-year Treasury bond). All data were sourced from the IMF's International Financial Statistics and World Economic Outlook databases

More specifically, the baseline for the LA-5 countries were as follows.

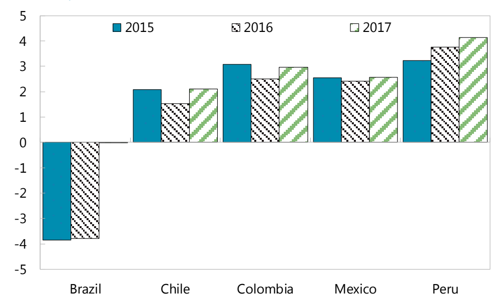
- Chile's growth was expected to slow to 1.5 percent in 2016, reflecting subdued confidence and sluggish investment in the mining sector, and to accelerate to 2.1 percent in 2017, partly reflecting further resolution of uncertainty related to the reform agenda. Despite relatively high leverage, firms have managed macroeconomic adjustment well so far—with largely hedged foreign exchange exposures—but deleveraging pressures are rising because of a protracted period of low demand and moderate competitiveness gains.

- Peru's economy had strengthened and growth was expected to rise further in 2016 (3¾ percent), boosted by ongoing investment in the mining sector but also reflecting resilience in other sectors.

- Colombia continued to grow at a relatively healthy rate, but output was projected to decelerate from 3.1 percent in 2015 to 2.5 percent in 2016, as a result of needed policy tightening and less favorable global financial conditions.

Figure 6. Baseline GDP Growth

(Annual percent change)



Sources: Fund staff estimates and projections

- In Brazil, a combination of macroeconomic fragilities and political problems had dominated the economic outlook. Economic activity contracted by 3.8 percent in 2015 and was projected to decline again in 2016 at the same rate. With many of the large shocks from 2015–16 were expected to have run their course, and helped by a weaker currency, sequential growth was projected to turn positive during 2017; nevertheless, output on average was expected to remain unchanged from the previous year.

- Mexico was expected to continue to grow at a moderate 2.4 percent in 2016, supported by healthy private domestic demand and spillovers from a strong U.S. economy. The recent decline in oil prices was expected to have only a limited effect on public finances in 2016 because the oil price risk had been hedged for the year. However, if the oil price shock were persistent, it would increase the fiscal consolidation burden in the medium term.

Distress scenario

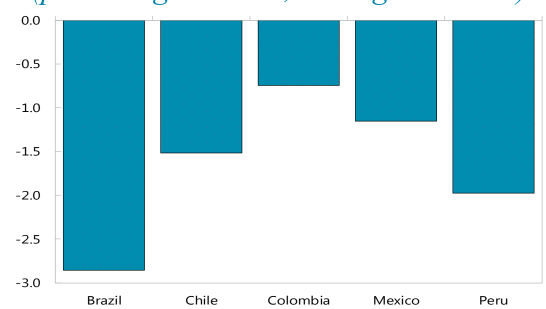
The distress scenario shocks the baseline scenario with a large drop in commodity prices. While there are several advanced methods to generate adverse scenarios, we opted for a simple statistical approach.[12] Specifically, it assumes that commodity prices will fall to the bottom 25th percentile of their empirical distribution over the period 2000 Q1 and 2017 Q4 as forecasted in the WEO baseline. This implies a quarterly price decline of 15½ percent staring at the end of 2016, with oil prices reaching a bottom of USD 19.3 per barrel, and the metal price index to 51.7 (2005 = 100) by end-2017.[13]

For simplicity, the distress scenario assumes that the commodity price shocks do not affect global variables and no spillovers from the LA5 countries to the rest of the world are generated. Once the distress scenario for commodity prices is set, the distress-level of domestic variables (GDP and exchange rate) are estimated through a country-specific VAR.[14] Figure 8 illustrates the dynamics of commodity prices, real GDP and exchange rates under both the baseline and distress scenarios.

To illustrate the magnitude of the shock, Figure 7 shows the impact on GDP across the countries in the sample. On average, GDP will be 1.7 percent lower during 2016-2017 across the five countries on the sample but with wide dipartites significant differences as Brazil's GDP will decline by about 2.9 percent while, on the other extreme, Colombia's GDP will decline only be about 0.7 percent.

Figure 7. Distress Scenario Impact on GDP Levels

(percentage decline, average 2016-17)



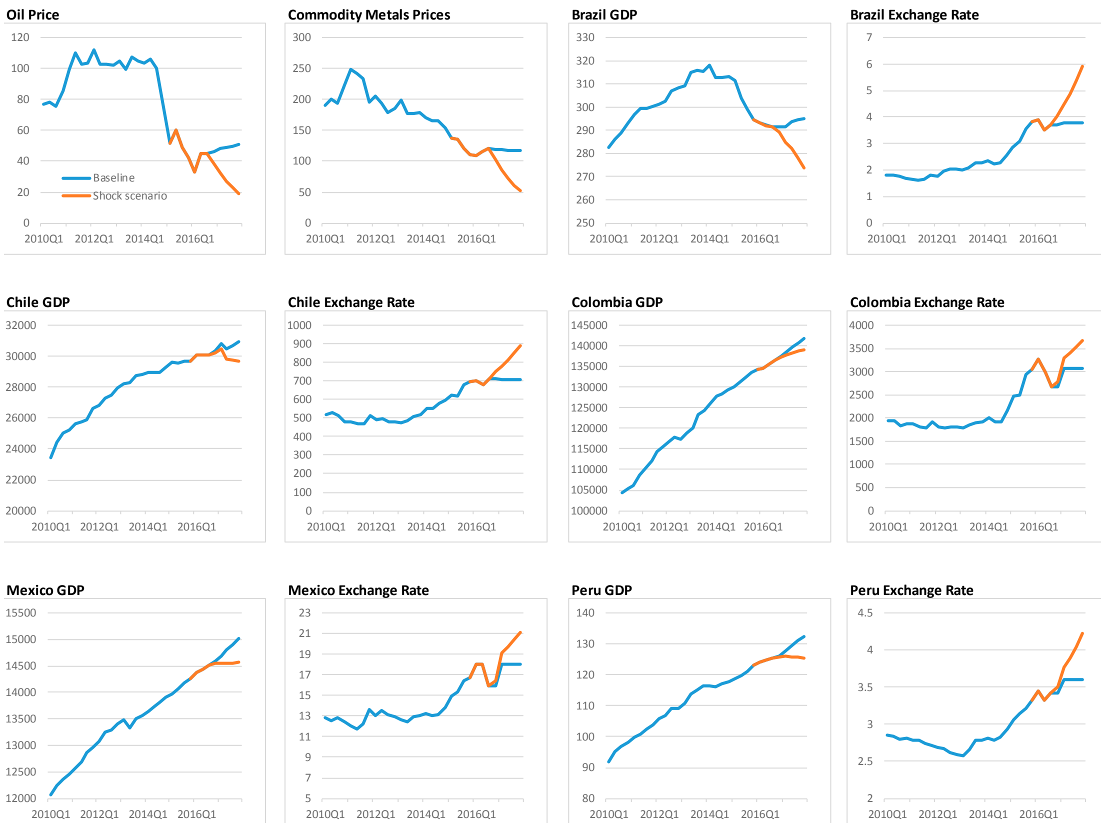
Source: Author's calculations.

[12] See Breuer, Jandacka, Rheinberger, and Summer (2009), Glasserman, Kang, and Kang (2015), and Chan-Lau et al, forthcoming, among others.

[13] The scenario assumes severe commodity price declines beyond what the baseline scenario contemplates but short of the realization of a tail event. In this sense, it differs from the type of scenarios central banks and policy making institutions use when they stress test banking systems, as described in Siddique and Hasan (2013), among others.

[14] A country-specific Vector Autoregressive (VAR) is used to project the paths of the domestic variables in the distress scenario. The endogenous variables are the real GDP growth rate and the exchange rate, and the exogenous variable is the key export commodity price, which is oil for Colombia and Mexico, and metals for Brazil, Chile, and Peru. The VAR is estimated in first differences to ensure stationarity. To generate the distress scenario for GDP and the exchange rate, we first forecast them conditional on the baseline scenario, and second conditional on the commodity price shocks. The difference between the two forecasts is added to the baseline scenario to obtain the distress scenario.

Figure 8. Baseline and Adverse Scenario: Commodity Prices, Real GDP and USD Exchange Rates



Implications of the Macroeconomic Scenario for Probability of Defaults (PDs)

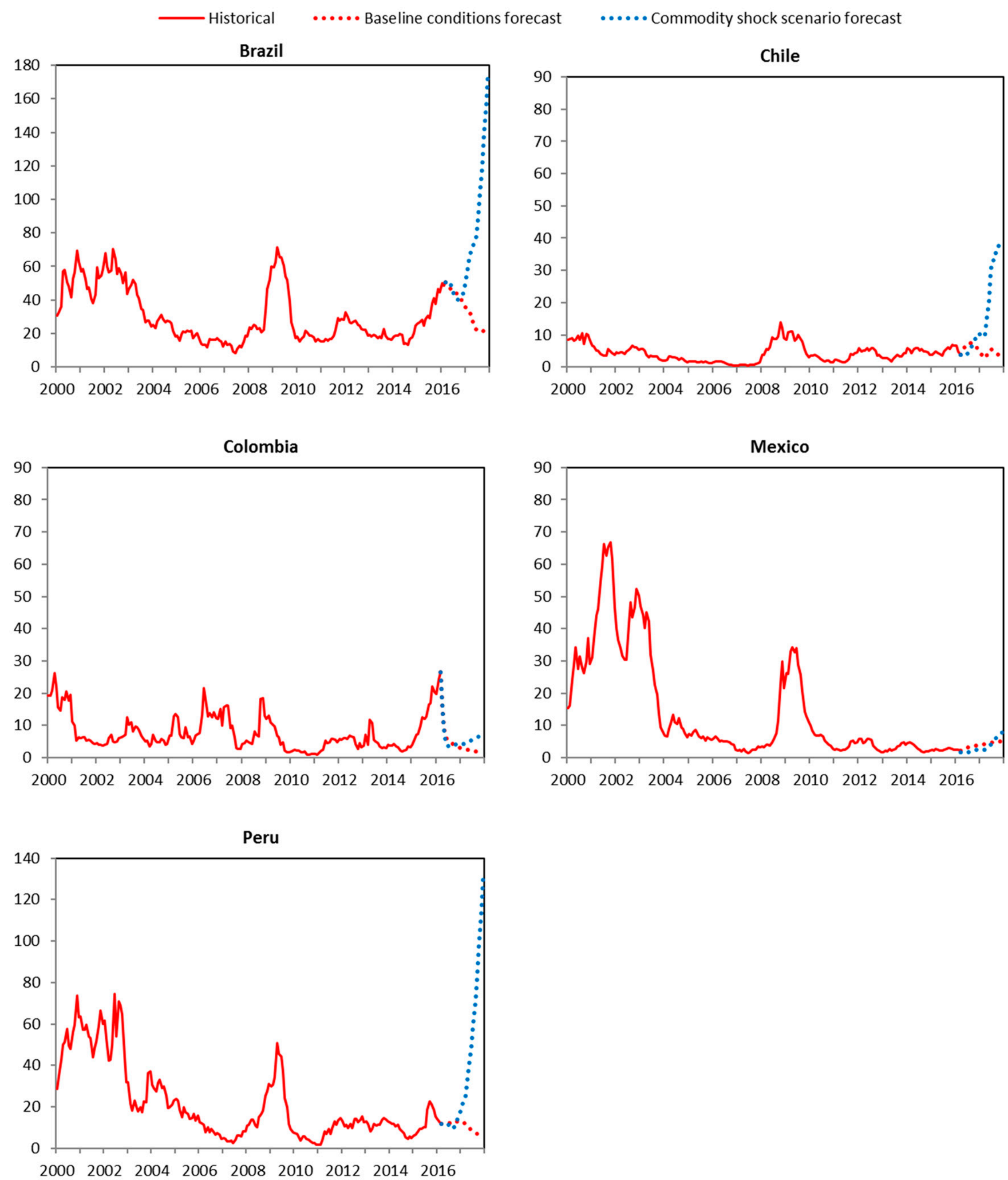
Baseline Scenario

Figure 9 shows the 12-month projected median PD of the corporate sector in the LA-5 countries under the baseline scenario. While the earlier analysis of financial ratios forewarned a worrisome increase in debt stocks and concentration, as well as declining revenue and profitability, the results of the baseline scenario suggests a more nuanced reading. In fact, PDs decline across the board for the LA-5 in the sample period mainly because economic activity in these countries was improving under the baseline scenario. In Peru, a rebound in exports and higher public investment, supported by cheaper financing for firms as the central bank cut the average reserve requirement, lowered PDs. In Mexico and Chile, the rise in foreign currency debt did not materially affect PDs, as most of the large firms reduced their exchange rate risks through a combination of natural hedges (revenues in foreign currency) and financial derivatives.

The decline in PDs was most distinct for Brazil and Colombia toward the end of the sample period. Brazil was recovering from a period of policy missteps and market uncertainty, with growth stabilizing and near-term prospects significantly brighter for business investment. Colombia was also recovering from the lingering effects of the economic slowdown in 2015 amid both weak global oil prices and slow growth in neighboring countries. PDs had spiked in early 2016 as corporate debt reached historical highs and vulnerabilities in the airlines and utilities sectors became apparent.

Figure 9. Probability of Default in the Non-Financial Corporate Sector

(Median probability of default in the next 12 months in basis points)



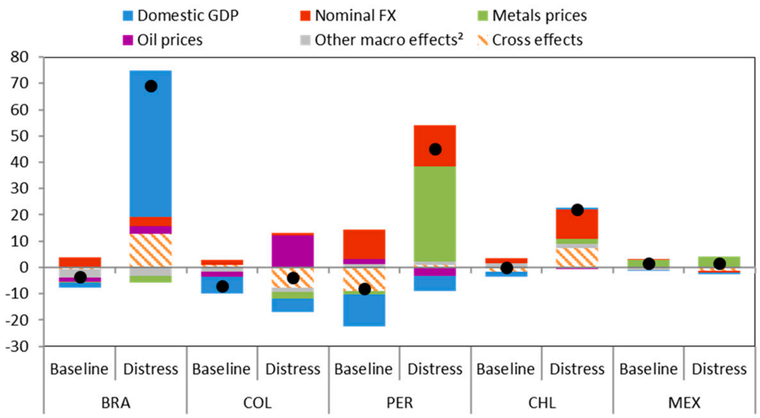
Sources: National authorities; Credit Research Initiative and IMF staff calculations.

Distress Scenario

The dynamics of the median PDs in the distress scenario is not homogeneous across the LA-5 countries despite the fact that the LAC-5 countries are all important commodity exporters and vulnerable to external shocks affecting their main trading partners and commodity prices. Brazil, Chile, and Peru are hit hard with the PDs increasing rapidly to levels not observed since early 2000 (Figure 8 and Figure 11, right panel). In contrast, Colombia and Mexico only experienced a muted response. To better understand what drives the different PD responses requires disentangling the contribution of each macroeconomic variable to the projected PDs (Figure 10).

Figure 10. Contributions to Changes in Projected Corporate PDs, 2017[1]

(Median probability of default in basis points)



[1] Changes compared to the scenario where the values of the macro variables are fixed at their Dec-2015 levels.
[2] Includes effects of advanced economies' growth and US interest rates.

- In Peru, the decline in metal prices was the primary reason for the sharp increase in PDs. The country is a major world exporter of metals such as copper, gold, zinc, and tin.

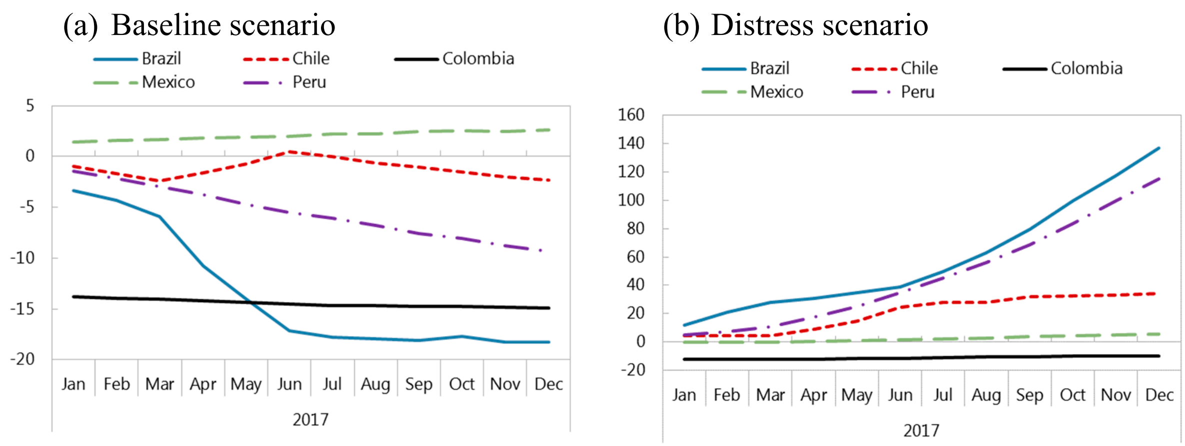
- In Chile, the depreciation of the nominal exchange rate as a result of the commodity price shock combined with high levels of foreign-currency denominated debt was the main factor in driving up PDs.

- In Brazil, the decline in commodity prices significantly affected GDP growth, which given the fragility of the recovery, caused a rise in PDs.

- In Colombia, the increase in PDs is less pronounced because GDP growth held up well despite the decline in commodity prices. In fact, Colombia is the only country where GDP growth remains positive in the distress scenario, due to the overall strength of the policy framework and built-in smoothing rules such as the structural fiscal rule and the flexible exchange rate.

- In Mexico, the PD reaction to the shock was also negligible, because both domestic and external demand were largely unchanged, and the non-commodity export-oriented sector continued to perform well even under the distress scenario. Indeed, the recent financial stability assessment (FSAP) of the country suggests that external developments are the main drivers of the performance of the corporate and banking sectors (IMF, 2016f).

Figure 11. Changes in Projected Corporate PDs (in basis points)
(Compared to 12-month average ending in March 2016)



B. Calculating Bank Provisions and Capital Buffers

Table 3 presents the results for both the baseline and distress scenarios. The starting value of the banking sector provisions and capital was end-2015; these values change as PDs evolve in accordance with standard risk management practices. As explained in more detail in the annex, provisions provide buffers against expected losses and capital against unexpected losses. The paper relies on the Basel formula for default correlation and the Vasicek one-factor model to generate the loss distributions. Therefore, economic capital, in our analysis, might not be equal to economic capital calculated using risk-weights.

With declining PDs in the baseline scenario, all LA-5 countries, with the exception of Brazil, show a decline in the average level of provisions over the 2016–7 period. In Brazil, the higher level of PDs, albeit declining, implies the need for creditors banks to hold higher provisions against solvency risk compared with 2015 levels even under the baseline scenario. Obviously, some caveats apply in the interpretation of the results below, as they represent a rough approximation to creditor banks' actual corporate loan portfolios.

Table 3. Required Provisions and Economic Capital
(In percent of GDP)

(a) Baseline scenario

	Provisions		Economic capital	
	2015 1/	2016-17	2015 1/	2016-17
Brazil	1.3	1.9	3.7	3.7
Chile	1.4	1.3	7.6	8.5
Colombia	1.2	0.8	4.7	3.8
Mexico	0.4	0.3	2.3	3.0
Peru	0.6	0.6	4.4	4.0

1/ Provisions (capital), as of October-2015, against corporate loans, estimated as total provisions (capital) multiplied by the ratio of commercail to total loans.

(b) Distress scenario

	Provisions		Economic capital	
	2015 1/	2016-17	2015 1/	2016-17
Brazil	1.3	2.0	3.7	4.9
Chile	1.4	2.7	7.6	12.3
Colombia	1.2	1.0	4.7	3.9
Mexico	0.4	0.4	2.3	2.2
Peru	0.6	0.9	4.4	5.7

1/ Provisions (capital), as of October-2015, against corporate loans, estimated as total provisions (capital) multiplied by the ratio of commercail to total loans.

In Chile, Mexico, and Peru, although provisions decline, higher asset correlations as implied by the Basel formula (equation (12), annex), lead to a higher economic capital requirement compared with 2015. In these countries, lower PDs generate lower expected losses, and correspondingly, lower provisions. But the lower PDs generate higher asset correlation values, so the loss distribution widens, leading to higher VaR values, and higher economic capital charges of about 1 percent of GDP. In Colombia, a robust baseline projection for GDP growth drives the result, with a sharply declining PD, and therefore provisions and capital.

Under the distress scenario, the LA-5 countries see a marked deterioration in PDs requiring an increase in both provisions and capital buffers in Brazil, Chile, and Peru relative to their 2015 levels (Figure 9). In Chile, in particular, required provisions are twice as high as those available at end-2015. Relative to GDP, provisions would need to increase by about 1 percent of GDP in Brazil and Chile, and by ¼ percent of GDP in Peru, while economic capital would need to increase by 1½ percent and ½ percent of GDP respectively, in Brazil and Peru. In Colombia, with the economy continuing growing even under the distress scenario, provisions and economic capital actually decline as in the baseline scenario albeit to a lesser extent.

In Mexico, economic capital needs are lower in the distress scenario than the baseline scenario, somewhat counter-intuitively, mainly because of the negative relationship between asset correlation and PD described above. Nevertheless, to put this in further context, the results are in line with those presented in the Mexico financial stability assessment in 2016 (IMF, 2016). Despite different methods used and the severity of the stress scenarios in the assessment exceeded that of our scenarios, the banking sector could withstand large adverse hypothetical shocks. One factor contributing to the resilience was the large diversification of the banks' corporate loan portfolio.

V. Concluding Remarks

A comprehensive assessment of the solvency of the corporate sector benefits from assessing macro-financial linkages under different scenarios. An analysis based on a review of financial ratios and debt indicators alone cannot not provide a full picture of corporate vulnerabilities. In this paper, we explain how to use the BuDA methodology, which takes advantage of current information contained both in financial statements and security prices. The BuDA methodology is therefore a tool for monitoring risks in the corporate and banking sector in real time. The methodology uses modern default risk modeling techniques to project probabilities of default for publicly listed firms under different macroeconomic and financial scenarios. When combined with credit portfolio risk techniques, it is able to evaluate whether creditor banks hold adequate buffers to withstand potential losses in their corporate loan portfolios.

We put the analytical machinery of BuDA to work by examining the evolution of solvency risk in the non-financial corporate sector of the LA-5 countries at end-April 2016. We chose the date for illustrative purposes, as concerns about corporate leverage reached a peak at that time, so the results should be interpreted as a methodological example rather than an analysis of current and/or prospective conditions in the corporate and banking sector.

Even within the narrow framework of an illustrative example, some caveats apply and should be kept in mind. As with every market-based model, the precision of the results depend on how reliable market prices capture market expectations, and whether these expectations reflect economic fundamentals rather than distortiions such as illiquidity and market manipulation. The BuDA analysis only applies to publicly traded firms so it may not shed light on the risks of loans to non-listed firms, or consumer loans.[15] In this context, although financial ratio analysis is static, it could provide a broader coverage of the corporate exposure of banks.

Our analysis of banks' buffers required a number of simplifying assumptions since no detailed information about banks' corporate loan portfolios was available. When using these techniques, it should be noted that the required change in capital and provisions are only approximations. In particular, absent information on the behavior of asset correlation in the economic scenarios, we used as a shortcut the Basel formula that links it to the level of the PDs. This formula tends to offset the economic capital banks need as PDs rise, an outcome that we observed in our results. The model would provide better estimates of economic capital with better information on the behavior of corporate loan portfolios. Nevertheless, their behavior in what if scenarios provide important information about how changes in corporate solvency risk lead to adjustments in the banking system's loss absorbency buffers.

[15] Stronger corporate governance and information disclosure requirements apply to listed firms than to unlisted firms. BuDA's PD projections, hence, could be interpreted as a lower bound on the PDs of unlisted firms. Though originally developed for publicly listed firms, it is possible to extend the DSW model to include privately held firms not traded in the market, as in Duan, Kim, Kim, Kim, and Shin (2014). Future work will aim to incorporate this feature in the BuDA model.

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A. Forecasting Risk Factors

BuDA obtains the risk factors for the LAC-5 economies directly from the internal RMI-CRI NUS database (CRI database). Table 4 shows the stock indices and short-term interest rates used for each LAC-5 country. Equity prices and financial statement data for individual firms in each country were sourced from Bloomberg LLP's Back Office Product. For Brazil, Colombia, Mexico, and Peru, the data covers the period April 1996 – January 2016. For Chile, the sample period is somewhat shorter and covers the period January 1998 – January 2016.

Country	Stock Exchange Index	Short-term interest rate	Period used 1/
Brazil	Brazil Bovespa Stock Index	Andima Brazil Government Bond Fixed Rate 3 Month	04/03/2000 - Present
		Brazil CDB (Up to 30 day)	10/10/1994 - 04/02/2000
Chile	Santiago Stock Exchange IPSA Index	Chile TAB UF Interbank Rate, 90-day	
Colombia	FTSE All World Series Colombia Local	Colombia CD Rate, 90-day	
Mexico	Mexico Bolsa Index	Mexico CETES 90-day, secondary market	06/26/1996 - Present
		Mexcio CETES 91-day, AVGRET AT AUC	03/09/1989 - 06/25/1996
Peru	Bolsa de Valores de Lima General Sector Index	Peru Savings Rate	

1/ A blank period entry indicates that a single interest rate was used during the whole period.

Source: Credit Research Initiative, Risk Management Institute, National University of Singapore

For each country, the regression equations for the economy-wide risk factors assumes that their one-period difference depends only on its own lagged level values and the lagged values of the exogenous scenario variables:

$$\Delta X_{m,t} = \beta_{m,0}^{X} + \sum_{i=1}^{n} \beta_{m,k}^{X} Z_{k,t} + \sum_{j=1}^{p} \gamma_{m,p}^{X}\, X_{m,t-p} + \epsilon_{m,t}^{X}, \tag{1}$$

where Δ is the one-period difference operator, $X_{m,t}$ is the m-th economy-wide risk factor, $Z_{k,t}$ is the k-th economic or financial variable included in the macroeconomic scenario, and $\epsilon_{m,t}^{X}$ is the error term.

Modeling the individual firm-specific variables is more difficult, since it involves a high-dimensional or Big Data problem due to the large number of firms analyzed in a given economy. To bypass this problem, BuDA implements the two-stage regression proposed by Duan, Miao and Wang (2014). In the first stage, it forecasts the average value of the firm-specific risk factor for all firms in a given industrial group of the economy using a regression of the form:

$$\Delta \bar{Y}_{i,j,t} = \beta_{i,j,0}^{Y} + \sum_{i=1}^{n} \beta_{i,j,k}^{Y} Z_{k,t} + \sum_{j=1}^{p} \gamma_{i,j,p}^{Y}\, \bar{Y}_{i,j,t-p} + \epsilon_{i,j,t}^{Y}, \tag{2}$$

where $\bar{Y}_{i,j,t}$ is the i-th country-industry average of the j-th firm-specific risk factor at time t, $Z_{k,t}$ is the k-th economic or financial variable included in the macroeconomic scenario, Δ is the one-period difference operator, and $\epsilon^{Y}_{i,j,t}$ is the error term.

Note that in equations (1) and (2) the sample frequency of the risk factors is monthly while that of some of the economic variables is quarterly. Absent a transformation of the equations, missing data may affect the estimation results. Because the dependent variable is the one sampled at a higher frequency, it is not possible to use mixed-frequency methods such as MIDAS (Ghysels, Sinko, and Valkanov, 2007). BuDA addresses this problem using a novel time-aggregation method suitable for maximum likelihood estimation (Duan, Miao, and Wang, 2012).

Once the time-aggregated version of equation (2) is estimated, the second stage involves modeling the "distance" of individual firms to the industry average. The distance is the difference between the values of the individual firm's specific risk factor and the industry average:

$$d\left(Y^{k}_{i,j,t}, \bar{Y}_{i,j,t}\right) = Y^{k}_{i,j,t} - \bar{Y}_{i,j,t}, \tag{3}$$

where for firm k, in industry sector i, the value of its j-th firm-specific factor is $Y^{k}_{i,j,t}$, and the average value of the j-th firm-specific factor for the industry is $\bar{Y}_{i,j,t}$. BuDA assumes the distance follows an autoregressive process of order p, AR (p), estimated over a 2-year moving window. To reduce potential biases, the estimation of the autoregressive process uses the Smoothly Clipped Absolute Deviation (SCAD) penalty proposed by Fan and Li (2001), which works as well as an oracle procedure for variable selection.[16]

The risk factors of individual firms are forecasted for each of the simulation rounds in the baseline and distress scenario, as explained in the next section. Due to the large number of firms analyzed, we do not report individual forecasts under each scenario.

B. Projecting PDs Using BuDA

The Forward Intensity Model

BuDA uses the DSW model to calculate the PD of individual firms using as input the forecasts of the risk factors. The DSW model is a reduced form model in the spirit of Duffie, Saita and Wan (2007) but it allows firms to exit for reasons other than default. This is an important but somewhat neglected feature in earlier PD models: the "survival" of a publicly listed firm requires that the firm remains listed in the exchange and has not defaulted. Since exit for other reasons greatly exceeds the number of defaults, an accurate default prediction model requires modeling explicitly default and non-default exits.

[16] In other words, the proper choice of the regularization parameter allows models estimated using the SCAD penalty to perform as well as if the correct model is known.

Default events fall under one of three different event categories:

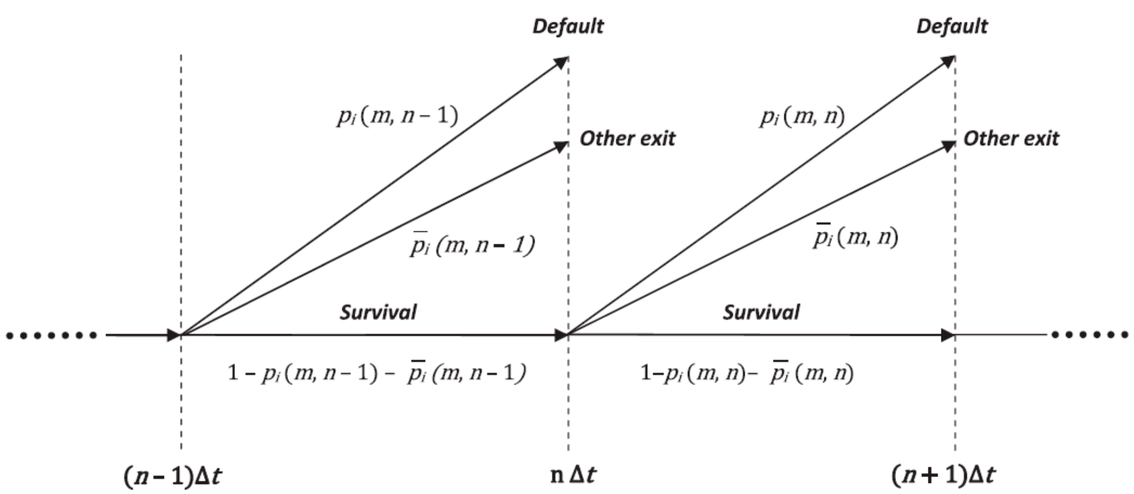
- Bankruptcy filing, receivership, administration, liquidation or any legal issue affecting the timely settlement of interest and/or principal payments.
- Missed or delay payment of interest and/or principal, excluding those made within a grace period.
- Debt restructuring/distressed exchange in which current creditors receive diminished financial obligations, either in terms of seniority and present value.

Other exit events include, among others, mergers and acquisitions, stock exchange delisting due to failure to meet listing requirements and/or listing fees, and selective capital reduction of the company.

The default and non-default exit processes are modeled using two independent Poisson processes, each with their own intensity function where the risk factors serve as inputs. This assumption allows for the realization of only one of three possible states at any point in time: survival, default, or non-default exit.

Figure 12 illustrates this situation in a discrete time framework, where $p_i(m, n-1)$ and $\bar{p}_i(m, n-1)$are the probabilities that the firm exits by default or other reasons between periods (n-1) Δt and n Δt respectively.

Figure 12: Default-other exit-xurvival tree for firm i, viewed from time t = mΔt



The figure highlights the dependence on past probabilities. For instance, the probability that the firm defaults between periods (n-1) Δt and n Δt measured at time $m\Delta t$ is:

$$\text{Prob}_{t=m\Delta t}[\tau_i = n, \tau_i < \bar{\tau}_i] = p_i(m, n-1) \prod_{j=m}^{n-2} [1 - p_i(m, j) - \bar{p}_i(m, j)] \,, \qquad (4)$$

where τ_i and $\bar{\tau}_i$ are the default time and other exit time measured in months. The cumulative default probability of defaulting at or before n Δt at time $m\Delta t$ is:

$$\text{Prob}_{t=m\Delta t}[m < \tau_i \leq n, \tau_i < \bar{\tau}_i] = \sum_{k=m}^{n-1} \{p_i(m, k) \prod_{j=m}^{n-2} [1 - p_i(m, j) - \bar{p}_i(m, j)] \}. \qquad (5)$$

For modeling purposes, the conditional probabilities of default and exit for other reasons are functions of their forward intensities, $h_i(m,n)$ and $\bar{h}_i(m,j)$, respectively:

$$p_i(m,n) = 1 - \exp[-\Delta t\ h_i(m,n)], \tag{6}$$

$$\bar{p}_i(m,n) = exp[-\Delta t\ h_i(m,n)]\big[1 - \exp[-\Delta t\ \bar{h}_i(m,n)]\big], \tag{7}$$

and where the forward intensities are exponentials of an affine function of the risk factors:

$$h_i(m,n) = exp[\beta(n-m).Z_i(m)], \tag{8}$$

$$\bar{h}_i(m,n) = exp\big[\bar{\beta}(n-m).Z_i(m)\big], \tag{9}$$

and β and $\bar{\beta}$ are coefficient vectors dependent on the number of months between the observation date and the beginning of the forward period (*n-m*), and $Z_i(m)$ is a vector collecting the economy-wide and firm specific risk factors together with a unit vector, i.e. $Z_i(m) = (1, X(m), Y_i(m))$. For details on the estimation, see Duan and Fulop (2013) and RMI-CRI NUS (2015).

The calibration of the DSW forward intensity model uses credit events and other exit data from the CRI database, where the compilation of credit events relied on several sources including Bloomberg, Compustat, CRSP, Moodys' Investor Services, exchange web sites, and news sources. For the LA5 countries, BuDA uses a model calibrated using emerging markets data.

Even if the scenario variables take fixed values there could be several possible paths for the PD of a firm due to the presence of random shocks in equations (1) and (3). Using simulation, the calibrated DSW model generate these paths using simulation. In each simulation, the firm-specific PD paths are aggregated to generate a realization of the median PD. The analysis uses the average value of the median PD over 1000 simulations.
The calibrated model serves to obtain multiple realization of the PD paths for each firm by simulation using equations (1) to (3), keeping the values of the scenario variables fixed.

Measuring the Contribution of Scenario Variables to the Projected PDs

BuDA is a highly non-linear model, and assessing the contribution of an individual variable to the projected PD in a scenario is not straightforward. Nevertheless, it is possible to isolate the contribution of each variable under the economic scenario with the following procedure.

- Estimate the benchmark PD, which is the median PD when all economic and financial variables are unchanged and set equal to their starting value. This generates a benchmark or "initial conditions" PD projection.
- Change one variable of interest while keeping all others unchanged, and project the PD.
- Subtract the benchmark PD from the individual variable PD. This difference is the PD contribution of the individual variable.

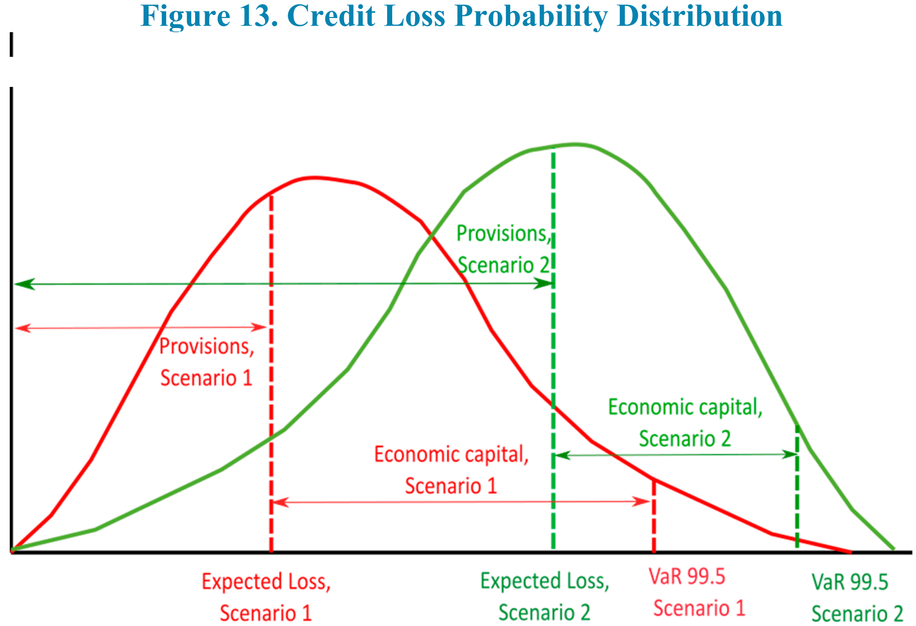
Due to the nonlinearity of the model, there is a cross-effect contribution to the PD projection due to the interaction between the variables that must also be taken into account. The PD contribution of the cross-effect is equal to the difference between the projected PD and the sum of the benchmark PD and the PD contribution of each individual variable. The cross-effects contribution to the PD projection captures the "residual" or interacting effects of all the variables that are not reflected in the benchmark or in the individual variable projections.

C. Calculating Bank Provisions and Capital Buffers

To analyze the linkages between solvency risk in the corporate sector and the banks' corporate loan portfolio, we assume that all banks in a country are homogeneous and hold an identical, granular, and stylized corporate loan portfolio. Each loan in the portfolio has a unit value, an identical PD, set equal to the average median PD in the economic scenario, and the same loss-given-default parameter, set equal to 40 percent.

The loss distribution of the portfolio, calculated using a single factor credit risk portfolio model, will be used to derive the provisions and economic capital for the corporate loan portfolio. Provisions correspond to the expected loss of the portfolio, and economic capital to the unexpected loss, that is, the difference between the Value-at-Risk for a high confidence level (99.5 percent) and the expected loss. Different economic scenarios would generate different PDs, and accordingly, different provisions and economic capital, as Figure 13 illustrates.

Figure 13. Credit Loss Probability Distribution



To calculate the loss distribution, we follow Vacisek (1987, 2002), and Gupton, Finger and Bhatia (1997), assuming that the asset value of the loan obligor, A_i, follows a standard normal distribution. The obligor defaults when its asset value falls below a certain threshold,d_i, whose value depends on the obligor's PD_i:

$$\text{Default if and only if } A_i \leq d_i \equiv N^{-1}(PD_i), \tag{10}$$

where N^{-1} is the inverse of the standard normal distribution. Loan defaults are correlated since the one-factor model assumes asset values are dependent on a systematic factor, *S*:

$$A_i = \rho S + \sqrt{1-\rho^2}\varepsilon_i, \tag{11}$$

where ε_i is an idiosyncratic shock and ρ is the firm's asset value correlation with the systematic factor. Both ε_i and *S* are uncorrelated, standard normal variables. Consistent with the homogeneity assumption, the correlation coefficient is the same for all loans.

Equations (10) and (11) enable the estimation of the loss distribution using simulations. In each simulation realization, we draw a random realization of *S*, and for each loan in the portfolio, draw a random realization of ε_i and calculate the asset value of the firm using equation (11), and verify whether the loan defaults are based on equation (10). The losses are added up to obtain one loss realization.

The only missing element for performing the simulations is assigning a value to the correlation coefficient, ρ. We follow the Basel Committee on Banking Supervision recommendations (BCBS, 2005), which are based on historical data, and assume the asset correlation is dependent on the *PD,*

$$\rho = 0.12 \times \frac{1-\exp(-50 \times PD)}{1-\exp(-50 \times PD)} + 0.24 \times \frac{(1-(1-\exp(-50 \times PD)))}{(1-\exp(-50))} \ . \tag{12}$$

It is important to keep in mind that the Basel formula establishes a negative relationship between PDs and asset correlations. The lower the PD, the higher the asset correlation; and vice-versa. This is because the higher the probability of default, the higher the idiosyncratic risk components of the firm. Provisions are directly related to PDs, so they increase when PDs increase. Capital depends on the PDs and the asset correlation. When assets are highly correlated, it is more likely to observe a larger number of loans (firms) defaulting simultaneously. This generates a loss distribution with fat tails, i.e. a large number of defaults. Capital is used as a buffer against tail losses, so high asset correlations drive capital up. Declining PDs would have the opposite effect. The Basel formula, hence, by establishing a negative relationship, leads to two counteracting forces. In the analysis, when the higher asset correlation prevails, the following results are observed:

PD down, asset correlation up -> provisions down, capital up
PD up, asset correlation down -> provisions up, capital down

Figure 6 illustrates this phenomenon: scenario 1 corresponds to a low PD case and scenario 2 to a high PD case. Provisions are higher in scenario 2 but economic capital is lower, as the distribution exhibits less dispersion.

For each country in the sample this analysis uses a stylized portfolio of 10 000 loans and 5000 simulations to calculate approximately the required economic provisions and capital for the aggregate banking system.

Implementing the loss distribution model requires an initial calibration of the provisions and bank capital. We set the initial values to those observed at end-2015 for country-aggregate provisions and bank capital data sourced from the IMF's Financial Sector Indicators (FSIs) database after scaling them down to reflect the share of corporate loans in banks' loan portfolios, since the latter also include non-corporate exposures, especially household loans.

For the calculation of the loss distributions, the credit portfolio model used the backward-looking 12-month average of the median PD rather than the point-in-time PD value. This assumption attempts to capture market practices, which use smoothed risk parameters, or through-the-cycle parameters, for building provisions and capital buffers. The results, hence, refer to the economic provisions and capital buffers calculated as through-the-cycle provisions and capital respectively.