1. Technical Note on Asset Valuation Models[1]

Asset price misalignments—deviations of asset prices observed in markets from those implied by economic fundamentals—could be an important source of risk for the financial system. Large price misalignments tend to increase the risk of a sudden and significant repricing of assets. This—depending on the extent of other financial vulnerabilities and buffers—could trigger substantial losses for investors and financial institutions. The knock-on effects such as fire sales of other assets or falls in valuations of collateral used for securities financing transactions could have implications for financial stability and for the broader economy.

The models used in the Global Financial Stability Report (GFSR) aim to (1) provide a direct measure of misalignment based on economic and corporate fundamentals, excluding—to the extent possible—market price-based measures (which could themselves include misalignments); and (2) be tractable and applicable to many international markets.[2]

This note describes the asset valuation models presented in the October 2019 GFSR, which includes models developed for: (1) several major advanced and emerging equity markets; (2) the US option-implied equity volatility index (VIX); (3) US and euro-area corporate bond spreads; and (4) emerging market foreign-currency denominated sovereign bond spreads.

Global Equity Markets[3]

The equity valuation models presented in this report are based on the dividend discount model (DDM), which explains equity prices as a function of expected corporate earnings, the compensation required to take on equity risk (the equity risk premium), and interest rates.[4]

Theoretical Background

According to DDM, the value of a stock is the present discounted value of its expected dividends, so that the price of equity is:

$$P_t = \frac{D_{t+1}}{k_t - E\{g_t\}} \quad (2)$$

[1] This note was prepared by Sergei Antoshin, Andrea Deghi, Rohit Goel, Thomas Piontek, and Akihiko Yokoyama.

[2] Though IMF staff tested the models for robustness and selected the best performing variables, the approaches are subject to limitations and uncertainty arising from, among other things, the definition and selection of fundamental factors, as well as possible alternative specifications and models.

[3] This section was prepared by Sergei Antoshin and Andrea Deghi.

[4] These models are similar to the US equity market model presented in the October 2018 GFSR.

where D_{t+1} is the dividend at time t+1, k_t is the cost of capital, and $E\{g_t\}$ is the dividend's anticipated steady-state growth rate.[5] What follows is a derivation of an estimation model based on Durham (2013). The cost of capital can be decomposed as follows:

$$k_{\mathrm{t}} = Y_t + \theta_{\mathrm{t}} \quad (3)$$

where Y_t is the long-term interest rate, and θ_{t} is the equity risk premium. Then (2) becomes:

$$P_t = \frac{D_{t+1}}{Y_t + \theta_{\mathrm{t}} - E\{g_t\}} \quad (4)$$

The long-term interest rate can be decomposed as follows:

$$Y_t = E\{r_t^{sh}\} + \rho_{\mathrm{t}} \quad (5)$$

where $E\{r_t^{sh}\}$ is the expected path of the short-term rate and ρ_{t} is the term premium. Using equations (3) and assuming that $E\{r_t^{sh}\} \sim E\{g_t\}$, the standard DDM equation (4) becomes:

$$P_t = \frac{D_{t+1}}{\rho_{\mathrm{t}} + \theta_{\mathrm{t}}} \quad (6)$$

where the price is a function of expected dividends, plus equity and term premia.

Empirical Estimation

Both equations (4) and (6) can be used in empirical estimation, depending on the performance of the empirical models for a given country (explained below). The equations (4) and (6) can be estimated as follows:

$$P_t = \beta_0 + \beta_1\, E_t + \beta_2\, \theta_t + \beta_3\, I_t + \epsilon_t \quad (7)$$

where E_t is the expected future earnings (as the proxy for both D_{t+1} and $E\{g_t\}$)[6] and I_t is either Y_t in (4) or ρ in (6). In this model, the error term ϵ_t is the extent of price misalignment relative to these fundamentals. A positive (negative) error term can be interpreted as over-(under-) valuation (shown in Chapter 1).

Empirical proxies for the factors in the model are discussed in the empirical asset pricing literature.[7] Expected earnings E_t are typically proxied by the average (across analysts) forecasts of earnings over the next 12 and 18 months from IBES—a widely used source for these forecasts. The equity risk premium θ_{t} is unobservable and, as in Durham (2013), is proxied in the GFSR model by the standard deviation (across analysts) of earnings forecasts over the next 12 months and 18 months from IBES. The interest rate Y_t is the yield on general government bonds with different maturities. ρ_{t} is proxied by either the term premiums from 4- and 5-factor models as in

5 See Campbell and Shiller (1998) for further refinements of the model.

6 The DDM can be re-written as a model of the enterprise value (replacing the price) which depends on earnings (which replace dividends). In empirical tests, expected dividends performed worse than earnings.

7 See for example Binder and others (2010), Durham (2013), and Damodaran (2006).

Adrian, Crump and Moench (2013) or the term spreads measured as the differences between long-term (10-, 20-, and 30-year) and 3-month government bond yields.

The selection of Y_t versus ρ_t is based on the sign and stability of the coefficients and the goodness of fit (R^2) of the respective models. In particular, the term spreads outperform the interest rates in the cases of the United States and the euro area (in these two cases, the ACM term premiums perform similarly to the term spreads). Table 1.1 lists all variables used in the country-specific models.

Online Annex Table 1.1. Equity Valuation Models: Variables

<table>
<tr><th>Markets</th><th>Equity Prices</th><th colspan="2">Factor I
(Corporate Earnings)</th><th colspan="2">Factor II
(Equity Risk Premium)</th><th colspan="3">Factor III
(Term Premia and Interest Rates)</th></tr>
<tr><td>United States & Euro Area</td><td>National Equity Indices</td><td rowspan="2">Weighted average EPS 12 months forward</td><td rowspan="2">Weighted average EPS 18 months forward</td><td rowspan="2">12-month-forward weighted average standard deviation for EPS data</td><td rowspan="2">18-month-forward weighted average standard deviation for EPS data</td><td>10 Years - 3 Months Govt. Bond Yield</td><td>20 Years - 3 Months Govt. Bond Yield</td><td>30 Years - 3 Months Govt. Bond Yield</td></tr>
<tr><td>Germany, United Kingdom, Japan, China, Brazil, India</td><td>MSCI Indices & National Equity Indices</td><td>6 Months Generic Govt. Bond Yield</td><td>2 Years Generic Govt. Bond Yield</td><td>5 Years Generic Govt. Bond Yield</td></tr>
</table>

Sources: Bloomberg Finance L.P.; Thomson Reuters I/B/E/S; and IMF staff calculations.

For each country-specific model, an extreme bound analysis[8] is employed to evaluate the sensitivity of all potential measures to alternative variable selections. This entails running a number of regressions covering all possible combinations of the variables used to proxy each factor category. The final model-implied equity valuation corresponds to the weighted average of fitted value estimates across the various model combinations, where the weights correspond to the R^2 from respective regressions. This approach allows one to base the assessment on a range of model specifications, without committing to one particular specification.

Results

The estimation is carried out on monthly data for China, Brazil, the euro area, Germany, India, Japan, the United Kingdom, and the United States. These equity markets account for over 70 percent of global equity market capitalization. Overall, the procedure performs well, with an average R^2 of 80 percent across countries. Stationarity and cointegration tests,[9] which assess the stability of the coefficients, and other robustness tests were performed. Table 1.2 reports the

[8] See Durham (2002).

[9] The Durbin Watson statistics and the Dicky and Fuller test were used to verify the stationarity of the input variables and the residuals form Equation (6). For the Johansen cointegration test, refer to Søren (1991).

estimated misalignments as of August and the average explanatory power by country. In addition to the misalignments expressed in percent of the actual price level, the misalignments scaled by the historical price volatility are shown as well (and presented in Chapter 1).

Online Annex Table 1.2. Equity Valuation Models: Results
(As of September 2019)

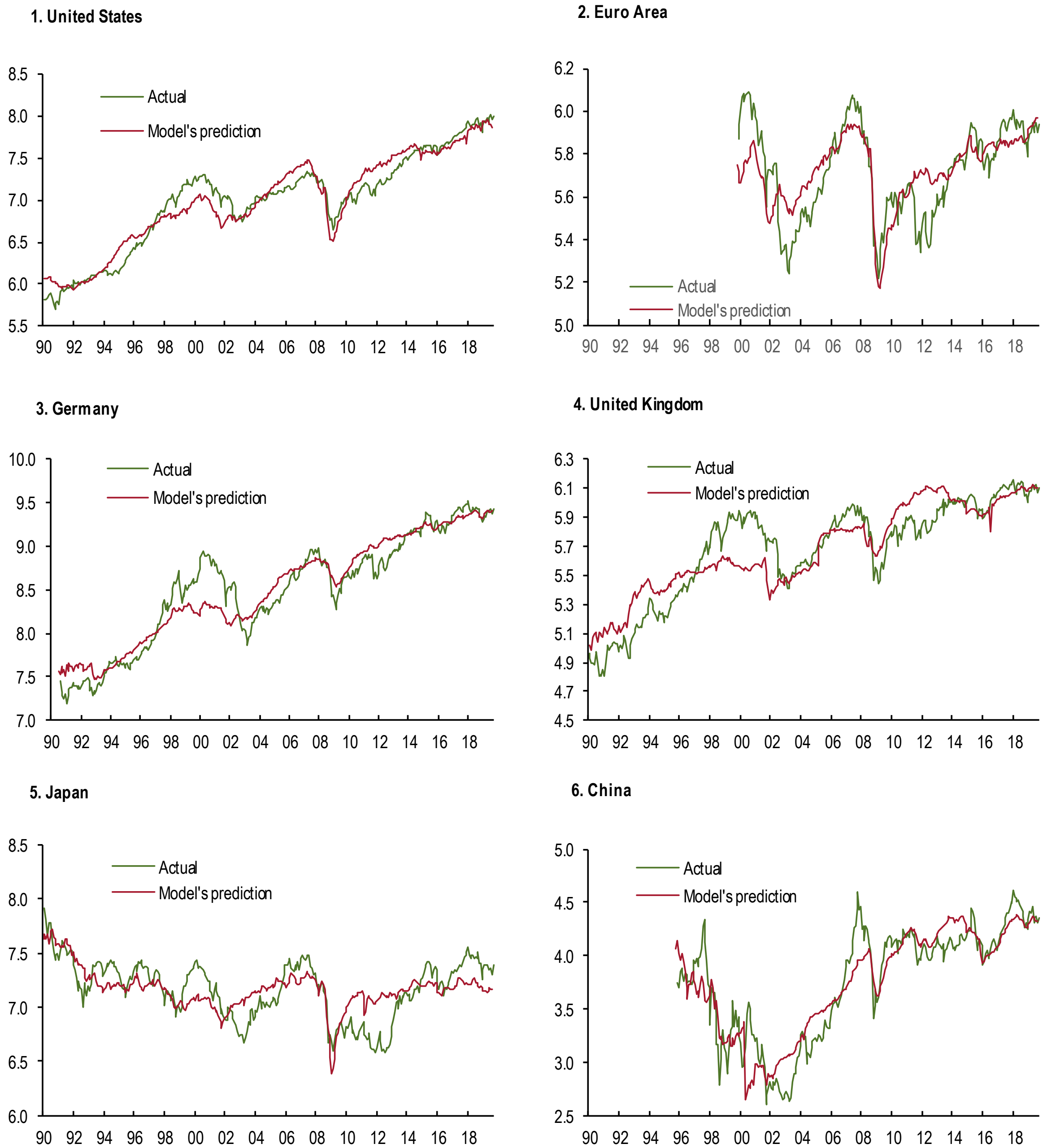
Market	Sample Start	Sample End	Monthly Oservations	Minimum R^2	Maximum R^2	Average R^2	Standard Error	Misalignment, Last Month (%)	Historical Volatility	Misalignment, Last Month Divided by Historical Volatility	Misalignment, Last Quarter Divided by Historical Volatility
United States	Jan 31, 1990	Sep 30, 2019	357	92%	93%	93%	1.0	15.1	4.2	3.6	2.6
Euro Area	Nov 30, 1999	Sep 30, 2019	239	51%	54%	53%	-0.2	-2.5	5.6	-0.4	-0.5
Germany	Aug 31, 1990	Sep 30, 2019	350	88%	89%	89%	0.1	1.6	5.9	0.3	0.3
Japan	Jan 31, 1990	Sep 30, 2019	357	42%	48%	45%	1.1	22.7	6.2	3.7	-0.1
United Kingdom	Jan 30, 1990	Sep 30, 2019	357	73%	79%	75%	0.0	0.2	4.4	0.0	2.9
China	Nov 30, 1995	Sep 30, 2019	287	80%	82%	81%	0.1	3.1	10.4	0.3	0.1
Brazil	Nov 30, 1999	Sep 30, 2019	239	91%	93%	92%	0.0	-0.1	7.0	0.0	-0.2
India	Apr 30, 1996	Sep 30, 2019	282	96%	96%	96%	0.2	3.6	7.8	0.5	0.6

Sources: Bloomberg Finance L.P.; Thomson Reuters I/B/E/S; and IMF staff calculations.

Figure 1.1 shows the historical misalignments by country. The confidence intervals are generally narrow and closely aligned with the fitted values, corroborating the robustness of the models.

Online Annex Figure 1.1. Equity Valuation Models: Results

(Equity indices; actual and fitted logarithm levels)



Sources: Bloomberg Finance L.P.; Thomson Reuters I/B/E/S; and IMF staff calculations.

US Option-Implied Equity Market Volatility[10]

Despite heightened policy uncertainty and rising global geopolitical risks, option-implied equity market volatility in the US has been relatively muted, despite occasional short-lived spikes. The VIX fair value model presented here aims to shed some light on the economic and financial factors that might be affecting market expectations of future US equity volatility. The model is similar to the one presented in the October 2017 GFSR.

Framework and Data

The analysis is centered on the US equity market, given that the US accounts for over one-third of the global equity market and heavily dominates trading of implied volatility instruments. The model utilizes several measures of uncertainty and indicators of financial market stress. The model is fitted using an ordinary least-squares regression, run over 16 years of quarterly data with the VIX as the dependent variable. All of the data series employed in the model are transformed to z-scores.

A set of eleven independent variables are grouped into the four categories (Table 1.3) that are discussed below:

- *Macroeconomic fundamentals:* A stable macroeconomic environment creates less dispersion of expectations for future economic performance. Low volatility in assets prices is in turn linked to lower volatility in forecasts about inflation and economic growth. The forecast dispersion of US inflation and growth are used as proxies for macroeconomic uncertainty and the change in the unemployment rate as a proxy for economic conditions.

- *Funding and liquidity conditions:* Periods of significant US financial stress can generate market volatility, such as during the financial crisis in 2007–09, while monetary policy accommodation can help support funding and liquidity conditions. Funding conditions are proxied by the difference between the three-month US Treasury bill yield and the three-month US dollar LIBOR rate (the TED spread). The forecast dispersion of US short rates is also included as an indicator of uncertainty regarding the outlook for short-term funding conditions. Net Federal Reserve purchases of US Treasuries is integrated as an indicator of central bank quantitative easing.

- *Corporate performance:* Corporate fundamentals have remained stable and contributed to steady investor earnings expectations. Cash-rich US corporations have used payouts via dividends and stock repurchases to smooth equity valuations, and thus compress volatility. Net income to assets and payouts to net income for S&P 500 firms are used as proxies for corporate performance.

- *External factors:* External spillovers emanating from spikes in geopolitical tensions and economic uncertainty in major foreign markets can also trigger higher asset price volatility. In 2015-16, China and oil worries have likely contributed to an increase in the VIX. Other

[10] This section was prepared by Thomas Piontek.

events include the eurozone crisis in 2010–12 and the more recent concerns about the outlook for global growth. The Sentix euro area economic sentiment index is used as a proxy for European financial stress and investor sentiment, while the volatility of the Citi global economic surprise index is incorporated as indication of broader global growth uncertainty. In addition, the rise of political and trade-related tensions can unsettle market calm, which is accounted for by including the trade policy uncertainty index.[11]

Online Annex Table 1.3. VIX Fair Value Model: Explanatory Variables

Area of Focus	Variables
Macroeconomic Fundamentals	Interquartile Range of One-Year Ahead US GDP Forecasts
	Interquartile Range of One-Year Ahead US CPI Forecasts
	U.S. Unemployment Rate Change (Year-over-Year)
Funding and Liquidity Conditions	Federal Reserve Net Purchases of US Treasuries
	Interquartile Range of One-Year Ahead US 3-Month T-Bill Forecasts
	TED Spread
Corporate Performance	Net Income to Assets for S&P 500 Firms
	Payouts to Net Income for S&P 500
External Factors	Rolling 12-Month Standard Deviation of Citi Global Economic Surprise Index
	US Trade Policy Uncertainty Index
	Sentix Euro Area Economic Sentiment Index

Sources: Bloomberg Finance L.P.; Federal Reserve; Haver Analytics; Philadelphia Federal Reserve Survey of Professional Forecasters; S&P Market Intelligence; and IMF staff calculations.

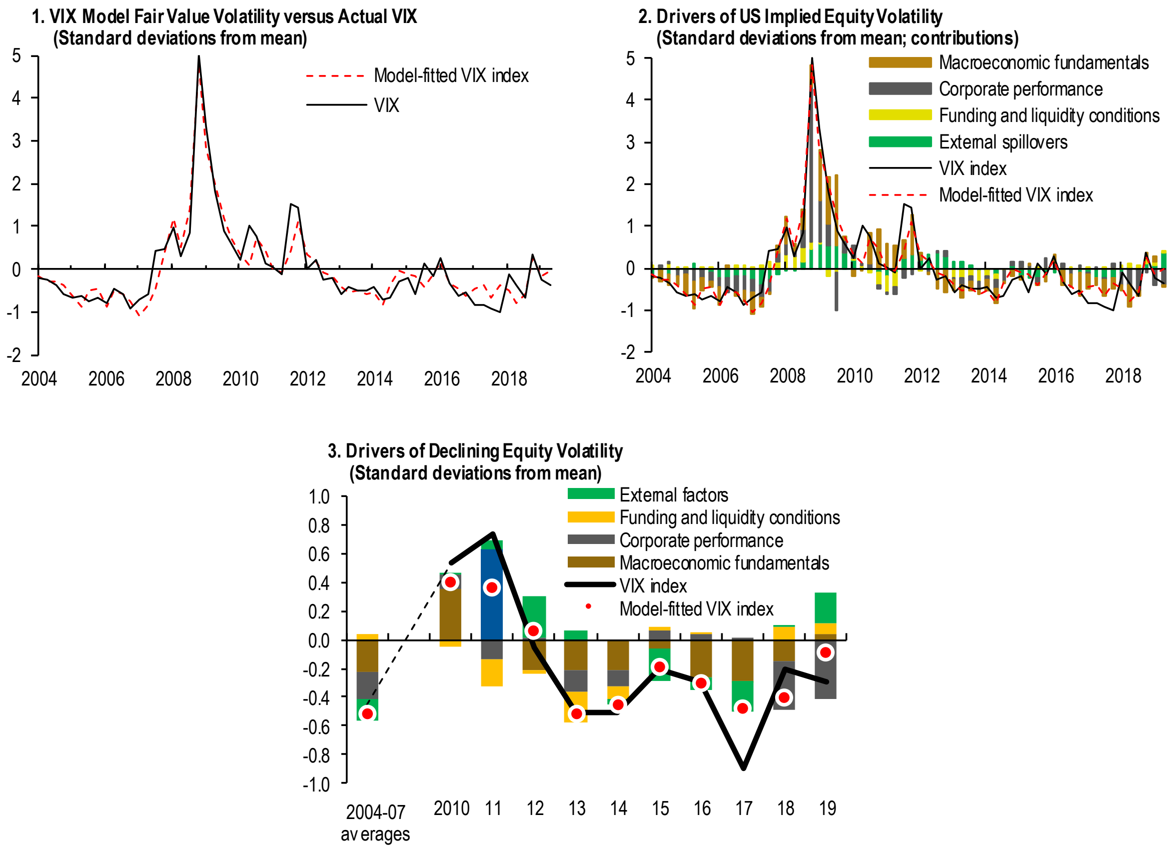
Results

The model provides a good fit for historical values of the VIX (Figure 1.2, panel 1). The results confirm that lower uncertainty about macroeconomic outcomes and corporate performance has been an important driver of implied equity volatility (Figure 1.2, panel 2). Based on the model, a substantial portion of the recent declines in implied volatility has stemmed from stable

[11] Based on the Baker, Bloom, and Davis US Trade Policy Uncertainty Index. The index reflects the frequency of articles in American newspapers that discuss policy-related economic uncertainty and contain one or more references to trade policy. See Baker and others (2016).

shareholder payouts and corporate performance that have contributed to steady investor earnings expectations. More recently, external factors such as trade tensions and uncertainty about the global economic outlook suggest that implied volatility should be higher than the average levels for 2019 (Figure 1.2, panel 3).[12] Part of this divergence could be due to a belief among investors that central banks will lean against a sharp tightening in financial conditions, hence implicitly providing insurance against significant declines in stock prices.

Online Annex Figure 1.2. Long-Run Drivers of US Implied Equity Volatility



Sources: Bloomberg Finance L.P.; Federal Reserve; Haver Analytics; Philadelphia Federal Reserve Survey of Professional Forecasters; S&P Market Intelligence; and IMF staff calculations.

[12] The VIX index was also compressed compared to the model-fitted VIX index in 2017. See the October 2017 IMF Global Financial Stability Report for further details on what the initial model calibrated as the drivers of the low level of the VIX index.

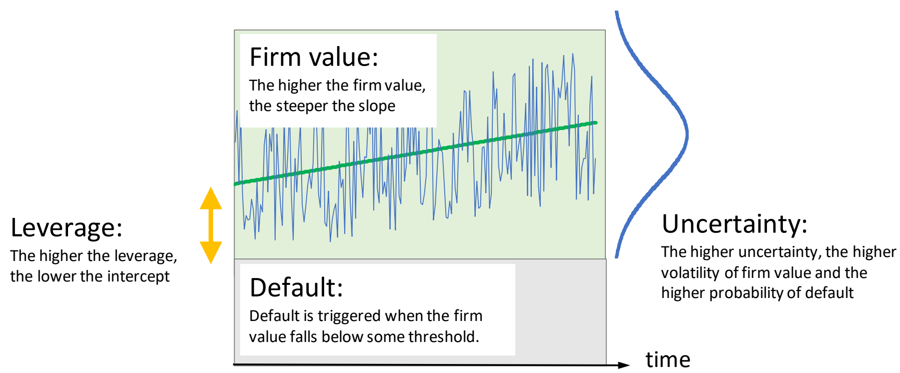
Corporate Bond Spread Valuations[13]

Corporate bond spreads—the difference between corporate and government bond yields—largely reflect the credit risk premium in the corporate bond market. This section explains the methodology used in the valuation models of corporate bond spreads in the US and the euro area corporate bond markets.

Framework and Data

Models of credit spreads usually assume that a key explanatory variable is default risk (which here encapsulates both the probability of default and the loss given default). Structural models of default provide a benchmark framework for identifying the determinants of credit spreads. The structural approach pioneered by Black and Scholes (1973) and Merton (1974) employs option pricing theory to model corporate debt valuations. By assuming that the firm value follows a stochastic process, they derive a relationship between credit spreads, leverage, volatility, and interest rates. In this framework, a firm defaults when its value falls below a certain threshold, which corresponds to the face value of debt (Figure 1.3).

Online Annex Figure 1.3. Structural Approach



Source: IMF staff.

Following the same intuition, the corporate bond valuation model used in this report is based on three groups of explanatory variables: economic (firm value) factors, uncertainty measures, and leverage metrics (Table 1.4). The approach adopts macro-economic indicators to proxy the firm value factors at an aggregate level. Corporate bond spreads are measured as the difference between the yield on the Bloomberg-Barclays corporate bond index and the duration-matched Treasury yield.

[13] This section was prepared by Akihiko Yokoyama and Andrea Deghi.

Following an approach that is similar to Collin-Dufresne et al. (2001) and Ericsson et al. (2009), the analysis uses monthly linear regressions to assess the relationship between corporate bond index spreads and the explanatory variables. Most empirical asset pricing studies of credit spreads consider a relatively small number of factors.[14] The factor variables used here are carefully chosen from a wide range of macro and financial variables using extreme bound analysis.[15] This entails running a number of regressions covering all possible linear combinations of the explanatory variables in each of the three groups: economic factors, uncertainty, and leverage. Each factor combination yields an estimate of the coefficients (β_j) and for each time t, a standard error term (ϵ_t). The procedure entails regressions of the form:

$$Corporate\ Bond\ Spread_t = \alpha_0 + \beta_1 Economic\ Factor_t + \beta_2 Uncertainty\ Factor_t + \beta_3 Leverage\ Factor_t + \epsilon_t \quad (1)$$

The variables chosen are robust to the unit root test and Johansen cointegration test. The final model-implied bond spread corresponds to the weighted average fitted value estimated across the various model combinations, where the weights correspond to the R^2 obtained from the respective regression.

Online Annex Table 1.4. Corporate Bond Spread Valuation Model: List of Explanatory Variables

	United States	Euro Area
Economic (Firm Value)	Expected GDP Growth Forecast	Expected GDP Growth Forecast
Factors	NFIB Small Business Survey	Mean Forecast EPS Growth Long Term (MSCI EMU)
	Industrial Production, Change Year on Year	Industrial Production, Change Year on Year
	Unemployment Tate, Change over Six Months	Unemployment Rate, Change over Six Months
Uncertainty	Probability of Recession	Probability of Recession
	Standard Deviation of GDP Growth Forecast	Standard Deviation of GDP Growth Forecast
	EPS Growth Forecast Dispersion Long Term	EPS Growth Forecast Dispersion Long Term
		EPS Forecast Dispersion 12 Months
		EPS Forecast Dispersion 18 Months
Leverage	Corporate Debt to GDP	Corporate Debt to GDP

Sources: Bloomberg Finance L.P.; Consensus Economics; Haver Analytics; Thomson Reuters I/B/E/S; and IMF staff calculation.
Note: Expected GDP growth is one-year ahead forecast calculated based on the data provided by Consensus Economics. EPS growth forecast is aggregated to all firm basis in the United States, to MSCI EMU firms basis in the euro area. Probability of recession is calculated based on the average and the standard deviation of analysts' one-year ahead forecasts of the real GDP growth assuming normal distribution. Recession is defined as GDP growth below zero percent. Data frequency is monthly. For the data available only on a quarterly basis, the latest data applied to the rest of months during the quarter. The sample period is from January 1995 to July 2019 for the United States, and from January 2004 to July 2019 for the euro area.

[14] See, for example, Huang and Huang (2002). Delianedis and Geske (2001) argued that credit spreads are mainly attributable to taxes, jumps, liquidity and market risk factors. Meanwhile, Ericsson et al. (2009) investigated credit default swap spread and found that the theoretical variables explain a significant amount of the variation in the data.

[15] See Durham (2002).

Results

The coefficients of economic factors in the benchmark model are negative, i.e., better economic conditions correspond to narrower corporate bond spreads, as the former lower the probability of corporate distress.[16] Coefficients of the uncertainty and leverage factors are positive, implying that higher uncertainty over future firm value and higher corporate leverage correspond to wider spreads. These results are consistent with Black and Scholes (1973) and Merton (1974). The share of the variation explained by the model is 60–70 percent, which is close to Ericsson et al. (2009). Table 1.5 reports the coefficients and the average R^2 across specifications. The coefficients apply to standardized independent variables.

Online Annex Table 1.5. Summary Statistics; Coefficients and R-Squared

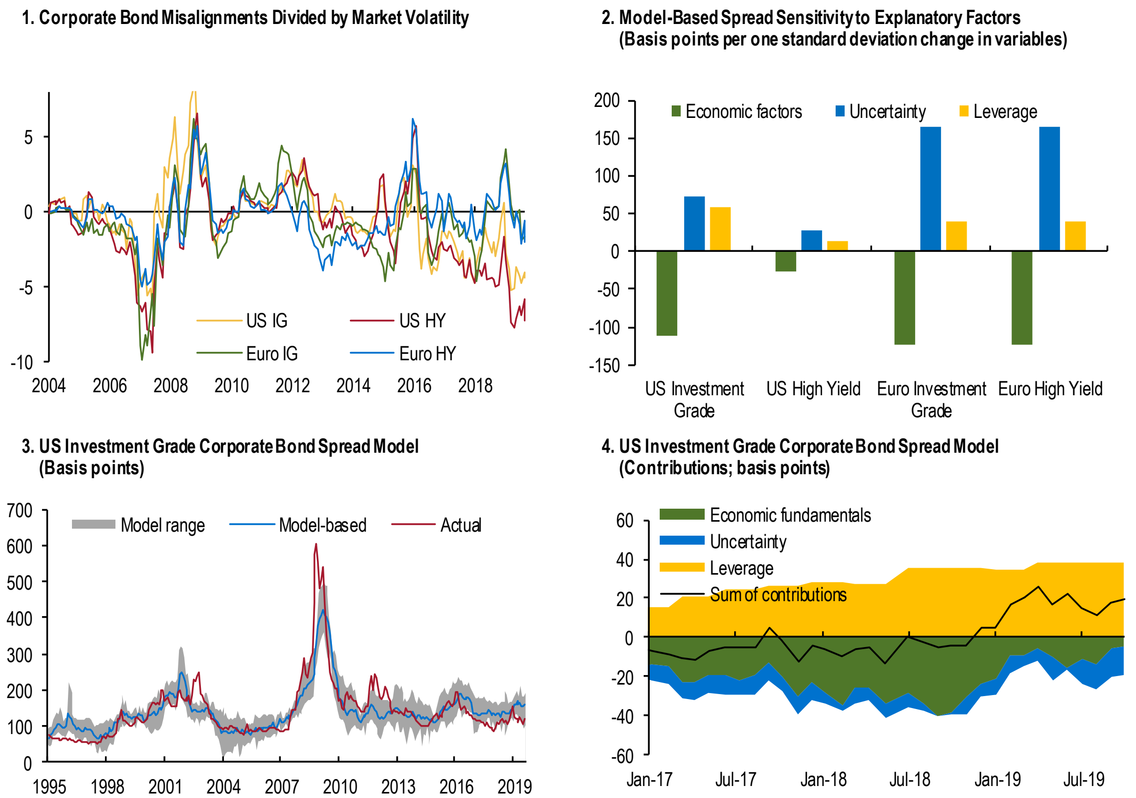
	US Investment Grade		US High Yield		Euro Investment Grade		Euro High Yield	
Independent Variable	**Avg. Beta**	**Avg. Rsq**	**Avg. Beta**	**Avg. Rsq**	**Avg. Beta**	**Avg. Rsq**	**Avg. Beta**	**Avg. Rsq**
Expected GDP Growth Forecast	-0.37	57%	-0.88	54%	-0.37	68%	-1.64	69%
NFIB Small Business Survey	-0.47	68%	-1.24	65%				
Mean Forecast EPS Growth Long Term (MSCI EMU)					-0.20	65%	-1.03	66%
Industrial Production, Change Year on Year	-0.42	58%	-1.18	58%	-0.20	65%	-1.31	69%
Unemployment Rate, Change Over Six Months	0.40	57%	1.19	59%	0.32	67%	1.25	65%
Probability of Recession	0.34	63%	0.99	61%	0.26	54%	0.94	55%
Standard Deviation of GDP Growth Forecast	0.24	60%	0.88	62%	0.45	62%	1.43	61%
EPS Forecast Dispersion 12 Months					0.64	80%	2.33	83%
EPS Forecast Dispersion 18 Months					0.61	79%	2.19	81%
EPS Growth Forecast Dispersion LT (All US)	0.12	57%	0.22	55%	0.24	57%	0.79	57%
Corporate Debt to GDP	0.18	60%	0.59	59%	0.34	66%	0.38	67%

Sources: Bloomberg Finance L.P.; Consensus Economics; Haver Analytics; Thomson Reuters I/B/E/S ; and IMF staff calculation.
Note: Average beta shows sensitivity of model spread to a unit change in explanatory variables, in percentage point.

Corporate bond spread misalignments are particularly large in the United States, though there is also some misalignment in the euro area corporate bond spreads (Figure 1.4, panel 1). Overall, model spreads are more sensitive to economic factors in the United States, and to uncertainty factors in the euro area (Figure 1.4, panel 2). For investment-grade corporate bonds (Figure 1.4, panels 3–4), the model-based spreads have been wider than the actual spreads throughout 2019, with the widening mainly driven by higher levels of corporate debt, and weaker economic fundamentals.

[16] An exception is the change in unemployment rate over six months for which the sign of its coefficient is positive (Table 1.2), as lower (or more negative) change in rates means more robust economic conditions implying narrower credit spreads. In the Figure 1.4, panel 2, the signs of coefficients for unemployment rate are reversed to be consistent with other variables.

Online Annex Figure 1.4. Corporate Bond Spread Valuation Model



Sources: Bloomberg Finance L.P.; Consensus Economics; Haver Analytics; Thomson Reuters I/B/E/S; and IMF staff calculation.
Note: Panel 1 shows the ratio of corporate bond spread misalignment to 36-month realized volatililty of spread (monthly change) in each market, which proxies dollar amount of potential losses relative to a unit of risk exposure. Panel 4 shows contributions of each factors to the model spread, relative to the long term average of actual spread.

EMBIG Spread Valuation Model[17]

Foreign-currency bond markets are a key external funding source for many emerging market borrowers as well as an important asset class for global investors. The amount outstanding of external government debt in emerging markets increased to $1.3 trillion in 2018 from only $0.5 trillion in 2008 (Dehn, 2019). Thus, any significant mis-pricing in this market could pose risks for both investors (valuation losses) and issuers (possible sharp changes in funding conditions). If bond spreads remain compressed relative to fundamentals for a long period, this may lead to an excessive buildup of debt by some borrowers with adverse implications for their future debt sustainability. Overvaluation also increases the risk of an abrupt adjustment in asset prices and possibly, capital outflows. This could further worsen market access, especially for lower-rated

[17] This section was prepared by Rohit Goel.

countries, and could make it difficult for countries to raise the funds they need at sustainable terms (Guscina, 2017).

The pricing of EM sovereign debt securities is linked to country-specific fundamentals but is also influenced by global investors' risk appetite. Risk appetite becomes especially relevant during periods of stress (González-Hermosillo, 2008), as it could interact with domestic vulnerabilities to amplify the impact on borrowers, especially those with weaker fundamentals. For instance, countries with weaker fundamentals were affected more significantly during the taper-tantrum episode in May 2013. Also, as discussed in the October 2018 GFSR, countries with high external debt were disproportionately affected by a sharp rise in the US dollar and higher US interest rates during April-September 2018.

Framework and Data

A fundamentals-based asset valuation model for EM hard-currency sovereign spreads[18] is constructed using both domestic fundamentals and external financial conditions. The model covers 71 emerging and frontier markets, across the five major regions, with quarterly data spanning back almost 25 years to December 1996. However, the time span is uneven, as countries entered the EMBIG Index in different years (as shown in Table 1.6). The data is sourced from Bloomberg; EM hard currency sovereign spreads are based on the JP Morgan bond indices.

Online Annex Table 1.6. Country Coverage and Data Availability

Africa		Asia Pacific		Europe		Middle East and Central Asia		Western Hemisphere	
Country	Data From	Country	Data From	Country	Data From	Country	Data From	Country	Data From
South Africa	Dec-96	Malaysia	Dec-96	Turkey	Dec-96	Morocco	Dec-97	Argentina	Dec-96
Nigeria	Dec-96	Philippines	Dec-96	Croatia	Dec-96	Lebanon	Jun-98	Brazil	Dec-96
Cote d Ivoire	Jun-98	China	Dec-96	Poland	Dec-96	Pakistan	Jun-01	Ecuador	Dec-96
Gabon	Dec-07	Indonesia	Sep-03	Russia	Dec-97	Egypt	Sep-01	Mexico	Dec-96
Ghana	Dec-07	Vietnam	Dec-05	Hungary	Mar-99	Tunisia	Jun-02	Panama	Dec-96
Senegal	Jun-11	Sri Lanka	Dec-07	Ukraine	Jun-00	Iraq	Mar-06	Colombia	Mar-97
Namibia	Dec-11	Mongolia	Jun-12	Serbia	Jun-05	Kazakhstan	Jun-07	Peru	Mar-97
Angola	Dec-12	India	Dec-12	Lithuania	Dec-09	Georgia	Jun-08	Chile	Jun-99
Zambia	Dec-12	Papua New Guinea	Dec-18	Belarus	Sep-10	Jordan	Mar-11	Uruguay	Jun-01
Mozambique	Dec-13			Romania	Mar-12	Azerbijan	Jun-12	Dominican Republic	Dec-01
Kenya	Sep-14					Armenia	Dec-13	El Salvador	Jun-02
Ethiopia	Dec-14					Oman	Jun-16	Belize	Mar-07
Cameroon	Dec-15					Tajikistan	Sep-17	Trinidad and Tobago	Jun-07
						Bahrain	Mar-19	Jamaica	Dec-07
						Kuwait	Mar-19	Guatemala	Jun-12
						Qatar	Mar-19	Costa Rica	Sep-12
						Saudi Arabia	Mar-19	Bolivia	Dec-12
						United Arab Emirated	Mar-19	Paraguay	Mar-13
						Uzbekistan	Mar-19	Honduras	Jun-13
								Suriname	Dec-16

Source: Bloomberg Finance L.P.
Note: Sovereigns with relatively limited history of spreads are highlighted in red.

[18] The spread is measured by how many basis points the treasury curve would need to be shifted upward in order for the discounted future cash flows of a bond to equal the market price.

Given data limitations, it is difficult to build reliable country-specific models, especially for countries that only have data available for a short period of time. Since spreads of many emerging and frontier market economies behave similarly under stress, the analysis focuses on panel estimation. An OLS model is estimated using an unbalanced panel.

The EM hard-currency bond spreads (EMBIG spreads) are regressed on domestic fundamental factors and external financial conditions, as follows:

$$Spread_{it} = c + \sum_{k=0}^{K} \beta_k * \ Fundamental_{kit} + \sum_{j=0}^{J} \alpha_j * \ GlobalRiskAppetite_t * Rating_j$$

where

- i (from 1 to 71) is the number of countries in our sample;
- k (from 1 to K = 7) is the number of fundamental factors (outlined below);
- j (from 1 to J = 8) is the number of ratings (AAA, AA, A, BBB, BB, B, CCC, and below)

and the fundamental determinants of the sovereign spreads are:

1. Domestic Real GDP growth – 1 year forward consensus forecasts
2. Domestic CPI Inflation – 1 year forward consensus forecasts
3. Current Account Balance (percent of GDP)
4. External Debt (percent of GDP)
5. Net Issuance of Foreign Currency Government Debt (percent of GDP)
6. Foreign Currency Reserves (percent of GDP)
7. External Real GDP growth – 1 year forward consensus forecasts

The global risk appetite factor is proxied by the US BBB corporate spread.[19]

Results

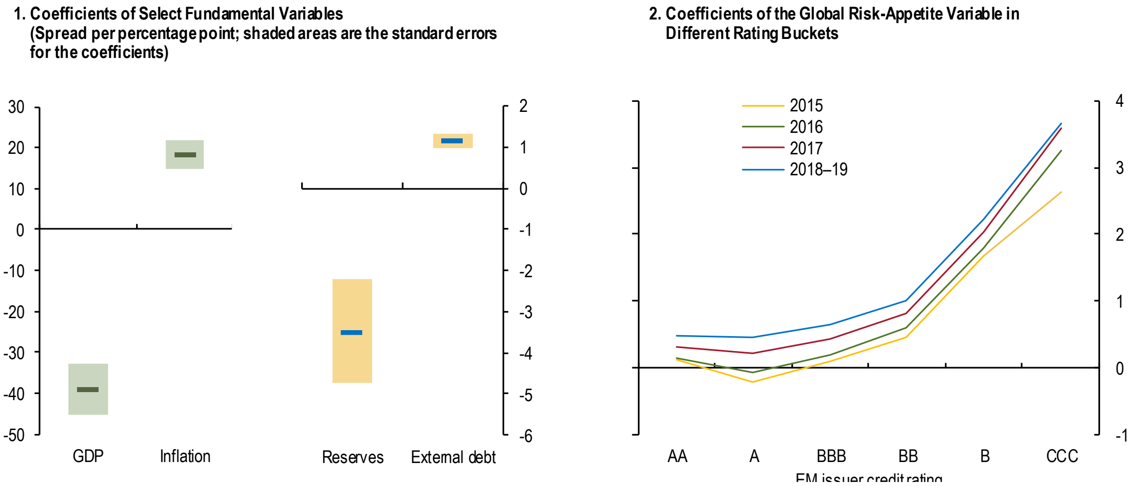
Domestic fundamentals are important in explaining EM hard-currency sovereign spreads. The analysis indicates that higher real GDP growth and lower inflation reduce sovereign spreads (Figure 1.5, panel 1). Similarly, higher reserves and lower external debt compress spreads. Figure 1.5, panel 1 plots the standard errors (±2 standard deviations) of the coefficients and all of them are statistically significant.

Lower-rated issuers are more sensitive to global risk appetite (Figure 1.5, panel 2). A 100 basis point increase in the US BBB corporate bond spread could widen spreads of B-rated EM bonds by more than 200 basis points, compared to only 50 basis points for A-rated EM issuers. Moreover, rolling regressions (over the last 24 quarters) show that the sensitivity of EM sovereign spreads to external conditions has risen significantly in recent years. Figure 1.5, panel 2 plots the coefficients of the sensitivity to global risk appetite for different rating buckets. The

[19] The US BBB corporate spread is a price-based measure meant to capture external factors pertaining to both economic fundamentals and other drivers, such as significant political events. As a market-based measure, the BBB US corporate spread can itself be misaligned. The results were broadly consistent using other measures of risk appetite such as the VIX Index.

impact from the global risk appetite variable has risen by more than 60 basis points over the last few years (as shown through the difference between the yellow and blue lines).

Online Annex Figure 1.5. Sensitivity of Model-Based Spreads to Selected Explanatory Variables

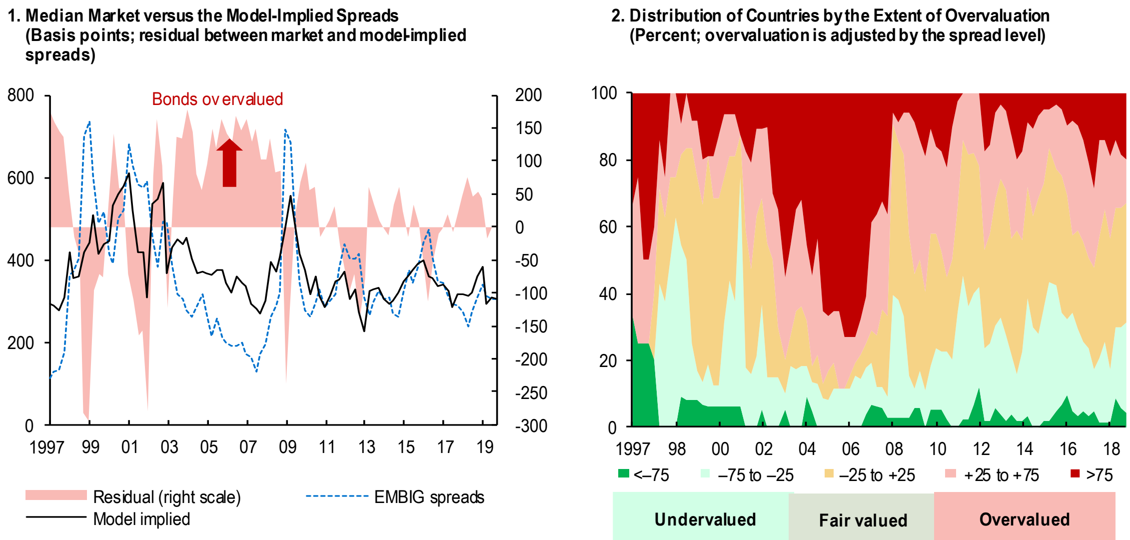


Sources: Bloomberg Finance L.P.; IMF, World Economic Outlook; and IMF staff estimates.

The analysis shows that EM hard-currency sovereign bonds were highly overvalued (spreads were too tight) before key stress events, including the Asian crisis (1998) and the global financial crisis (2008). While overvaluation can persist for a long period of time (Figure 1.6, panel 1), the correction can be swift and can lead to an abrupt tightening of funding conditions. As of September 2019, median spreads are broadly fair-valued. This contrasts with early 2018 when the EM foreign currency denominated bonds were, on average, overvalued (which may have exacerbated the EM sell-off that started in April 2018.) Finally, based on the distribution of countries based on the extent of overvaluation, almost 90 percent of EMs were overvalued before the global financial crisis, as compared to about one-third as of Q3:2019 (Figure 1.6, panel 2).[20]

[20] The results are broadly corroborated through other measures of overvaluation including a) residual difference between market and model implied spreads; b) historical percentile and; c) z-scores. The trends also remain relatively consistent when using other thresholds

Online Annex Figure 1.6. Estimated Misalignments in EM Hard-Currency Sovereign Bonds: 1997-2019



Sources: Bloomberg Finance L.P.; IMF, World Economic Outlook; and IMF staff estimates.

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2. Technical Note on the Credit Quality Assessment of the Corporate Sector[21]

This note describes the data and the methodology underpinning the corporate credit quality analysis in Chapter 2. The goals of this exercise are: (1) to build a comprehensive firm-level database for systemically-important economies; (2) to construct a number of credit-quality metrics based on firm-level balance-sheet data; (3) to extrapolate the sample's results to the whole corporate sector in each country; and (4) to project the evolution of the credit quality metrics for the period 2019–21, under an adverse scenario. The analysis is conducted for eight out of the 29 jurisdictions with systemically important financial sectors —China, France, Germany, Italy, Japan, Spain, the United Kingdom, and the United States—which represent the largest world economies.

This note discusses: (1) the sample and data sources; (2) the definition of speculative-grade debt for all firms in the sample; (3) the extrapolation of the sample's statistics to the corporate sector level; and (4) the scenario analysis.

Sample

Three comprehensive sources of firm-level data are used in this analysis: Bureau van Dijk Orbis, S&P Market Intelligence (CIQ), and WIND (for Chinese firms only). The data coverage varies greatly across the three databases, especially if the sample is divided by firm size (as discussed below). Only non-financial firms are included, and the public administration sector is excluded (see below). Based on the effective number of firms with data for 2016, Orbis has about 1.3 million firms, CIQ has 10 thousand firms, and WIND has 10 thousand Chinese firms. Table 2.1 reports the number of firms by source, country, and firm size.

For the purposes of our analysis, firms are sorted into three groups by size: *large* firms with assets exceeding 500 million US dollars, *medium* firms with assets between 50 million and 500 million, and *small* firms with assets below 50 million. Based on the above definition and the compositions of several key equity, bond, and leveraged loans indices, *large* firms can typically obtain any form of market financing (equities, bonds, and syndicated loans), *medium* firms can issue equity and syndicated loans (the latter is typical for bigger than average firms in this bucket), and *small* firms predominantly rely on loans from banks (although some can issue equity and very small firms use credit cards). Sectoral classification varies across the three databases. Firms are assigned to 6 major sectors by economic activity based on NACE codes in Orbis and to 10 major industries used by main equity indices based on GICS codes in CIQ and WIND. Table 2.2 presents the list of sectors.

[21] This section was prepared by Sergei Antoshin and Xingmi Zheng.

Online Annex Table 2.1. Corporate Sector Analysis: Sample by Source, Country, and Firm Size

(The number of firms in 2016)

	Orbis	CIQ	WIND	Orbis	CIQ	WIND	Orbis	CIQ	WIND	Orbis	CIQ	WIND
	All	All	All	Large	Large	Large	Medium	Medium	Medium	Small	Small	Small
China	289,232	3,811	10,486	2,916	2,635	3,160	13,102	1,131	2,405	273,214	45	4,921
Japan	146,739	2,339	-	1,427	945	-	7,039	1,129	-	138,273	265	-
United Kingdom	94,010	625	-	1,134	249	-	4,432	224	-	88,444	152	-
United States	2,690	2,259	-	1,457	1,402	-	604	520	-	629	337	-
France	234,929	355	-	424	129	-	2,603	106	-	231,902	120	-
Germany	22,047	339	-	424	143	-	2,406	120	-	19,217	76	-
Italy	236,015	223	-	380	66	-	3,801	93	-	231,834	64	-
Spain	326,005	146	-	352	65	-	2,642	40	-	323,011	41	-
Total	**1,351,667**	**10,097**	**10,486**	**8,514**	**5,634**	**3,160**	**36,629**	**3,363**	**2,405**	**1,306,524**	**1,100**	**4,921**

Sources: Bureau van Dijk Orbis; S&P Market Intelligence; WIND; and IMF staff calculations.

Online Annex Table 2.2. Corporate Sector Analysis: List of Sectors by Source

Orbis	
1	Food, Beverages, Tobacco, Chemicals, Rubber, Plastics, Non-Metallic Metals & Metal Products, Machinery, Equipment, Furniture, Recycling, Primary Sector, Wood, Cork, Paper, Textiles, wearing apparel, leather
2	Gas, Water, Electricity
3	Construction
4	Hotels & Restaurants, Transport, Wholesale & Tetail Trade
5	Post & Telecommunications, Publishing, Printing

Capital IQ and WIND	
1	Communication Services
2	Consumer Discretionary
3	Consumer Staples
4	Energy
5	Health Care
6	Industrials
7	Information Technology
8	Materials
9	Real Estate
10	Utilities

Sources: Bureau van Dijk Orbis; S&P Market Intelligence; WIND; and IMF staff calculations.

Speculative-Grade Debt

Two *measures of corporate credit quality* are used in the analysis: (1) debt-at-risk, defined as the debt owed by firms with an interest coverage ratio (ICR) below 1; and (2) speculative-grade debt, defined as the debt owed by firms with *implied* speculative-grade ratings based on the ICR and the net debt-to-assets ratio.[22] Both credit quality measures are calculated for all firms in the sample, regardless of whether a firm had issued debt in the market and whether it had an actual credit rating. The use of net debt instead of gross debt is motivated by the need to take into

[22] Net debt is gross debt minus cash. The ICR in both measures is calculated as EBIT-to-interest expense; EBIT is used instead of EBITDA because it is more commonly available.

account increased cash holdings in the nonfinancial sector in the period following the global financial crisis.

Next, the objective is *to separate firms with speculative grade debt characteristics from the ones with investment grade characteristics*. In principle, implied credit ratings can be assigned based on aggregate statistics provided by credit rating agencies.[23] Credit rating agencies report average financial statistics—including the ICR—for an average global firm by credit rating. It is, therefore, possible to define the thresholds for speculative grade firms by picking a mid-point between the statistics for BBB/Baa- and BB/Ba-rated firms.[24] For the purposes of our analysis, the thresholds are established empirically:

- The *sample* consists of about 6,600 investment grade bonds from the Bloomberg Barclays Global Aggregate Industrial Index (***LGCITRUU*** <Index>) and 2,200 speculative grade bonds from the Bloomberg Barclays US and Pan-European High Yield ex. Financials Indices (***I20675US*** and ***I20671EU***). The data on their credit ratings, EBIT, interest expense, debt, and cash are from Bloomberg.

- An *optimization procedure* is carried out to establish the thresholds for the ICR and net debt ratio by maximizing the proportions of correctly estimated ratings based on the thresholds. Based on this procedure, a firm has an implied rating of BB/Ba or lower if it has simultaneously the ICR below **4.1** and the net debt-to-assets ratio above **25** percent. The maximum success rate in this estimation is 68 percent. Table 2.3 presents the summary statistics and results of this exercise. The threshold for the ICR found using this method falls within statistical ranges reported by rating agencies. For example, Moody's (2017) shows that firms rated Baa and Ba have, on average, EBITA-to-interest of 6.5 and 3.9, respectively. The obtained thresholds are used to identify firms with speculative grade debt and to compute the share of speculative grade debt in the sample.

[23] For example, see the corporate debt overhang analysis in Chapter 1 of the October 2013 GFSR.

[24] However, the rating agencies' definitions of the ratios are not exactly the same as ours (as our goal is to use most commonly available data), and the calculation is not straightforward when two ratios are involved in the determination of the thresholds.

Online Annex Table 2.3. Credit Rating Analysis: Summary Statistics

(Based on bonds in Global Aggregate Industrial and High Yield excluding Financials indices)

	EBIT/Interest	Net Debt/Assets
Medians		
IG	6.8	30
HY	2.0	42
Weighted averages		
IG	7.8	31
HY	1.7	41
BBB	4.8	33
BB	2.6	38
Thresholds for BBB | BB		
Mid-point	3.7	36
Optimization	**4.1**	**25**
Success Rate	*67.8%*	

Memo: Moody's (2017)	*EBITA/Interest*
Baa	*6.5*
Ba	*3.9*
mid-point	*~ 5.2*

Sources: Barclays; Bloomberg Finance L.P; Moody's (2017); and IMF staff calculations.

Extrapolation to the System Level

After the sample's credit metrics are computed, the next step is to extrapolate the results to the system level. The uncertainty around system-level estimates arises because of: (1) different results for the samples from the three databases; and (2) the lack of visibility on the "true" distribution of firms by size in the overall corporate sector. In turn, the three databases yielded somewhat different results because of the variation in the samples' sizes and compositions and because of some differences in accounting conventions used by data providers.

Table 2.4 shows, as an example, the debt-at-risk based on EBIT-to-interest below 1 in 2016 by source, country, and firm size. Data validation for top companies showed that in some cases the three data providers either overestimated or underestimated interest expense.[25] However, there is no unidirectional bias in the results that persisted across countries or across firm sizes. For example, across countries, for large Chinese firms, CIQ has a higher share of debt-at-risk than Orbis does, but the opposite is true for large UK firms. As another example, across firm sizes, in Italy Orbis has a higher share of debt-at-risk for large firms but a lower share of debt-at-risk for SME compared to CIQ.

[25] The data from the three databases was compared to the data from Bloomberg.

Online Annex Table 2.4. Corporate Debt at Risk by Source, Country, and Firm Size

(Share of debt at firms with EBIT-to-interest below 1 in 2016)

	System	Sample	Sample	Orbis	CIQ	WIND	Orbis	CIQ	WIND	Orbis	CIQ	WIND	Orbis	CIQ	WIND
		Large	SME	Large	Large	Large	SME	SME	SME	Medium	Medium	Medium	Small	Small	Small
China	24%	23%	25%	24%	38%	8%	25%	34%	18%	23%	29%	18%	28%	38%	19%
Japan	11%	3%	20%	3%	3%		20%	20%		13%	10%		27%	29%	
United Kingdom	34%	32%	38%	34%	29%		38%	35%		42%	27%		35%	43%	
United States	38%	15%	64%	17%	13%		65%	63%		52%	51%		77%	76%	
France	24%	15%	38%	17%	11%		38%	49%		42%	21%		34%	76%	
Germany	22%	21%	24%	25%	12%		23%	40%		26%	30%		21%	50%	
Italy	23%	19%	28%	30%	3%		27%	39%		29%	43%		26%	35%	
Spain	28%	21%	34%	24%	16%		34%	73%		36%	67%		32%	79%	
Average	*25%*	*19%*	*34%*	*22%*	*16%*		*34%*	*44%*		*33%*	*35%*		*35%*	*53%*	

Sources: Bureau van Dijk Orbis; S&P Market Intelligence; WIND; and IMF staff calculations.

The results from the three databases are aggregated by firm size for each country using debt levels at each firm as weights. The overall sample's results are obtained for each country and firm size by aggregating the sub-samples from the three databases using the total debt in the three databases as weights. For example, given Orbis' extensive coverage of small firms, the overall sample's results for small firms are heavily affected by Orbis' statistics. All the three databases had a good coverage of large firms, so their weights are proportionate. Mid-size and small firms are included into one group (SMEs), where SMEs' debt and credit metric are the sum and the average, respectively, of the components for mid-size and small firms.

The issue of the lack of data by firm size in the overall corporate sector is difficult to resolve with certainty. Typically, the only breakdown of overall nonfinancial corporate debt available from public national sources is the split into corporate bonds and loans.[26] A key assumption driving the system-level results concerns the share of large firms in the overall corporate sector. Since the credit quality metrics are usually better at large firms (except in China), a larger share of large firms implies a better credit quality in the overall corporate sector. Four estimates of the share of large firms are obtained:

- The *high estimate* of the share of large firms is based on the sample's distribution, which is skewed towards large firms (as SMEs are underrepresented in most databases), and therefore, usually gives a more optimistic picture of the overall credit quality in the corporate sector.
- The *low estimate* of the share of large firms assumes that the sample fully captures large firms, so that the debt of large firms in the system equals that in the sample. This implies that the rest of the corporate sector (not captured in the sample) consists of SMEs, which tend to have weaker credit quality. This approach, therefore, usually gives a more pessimistic picture of the overall credit quality in the corporate sector.

[26] In France, aggregate corporate debt from national sources includes inter-company loans.

- The *central estimate* assumes that large firms' debt is the sum of total corporate bonds (because SMEs cannot issue bonds as discussed above) and half[27] of total loans.

- Finally, the *average estimate* is the average of the low and high estimates. In several cases, the central estimates of debt-at-risk are similar to the average estimates. The range of the estimates for the debt weight of large firms, and the corresponding results for debt-at-risk, are presented in Table 2.5.

Online Annex Table 2.5. System-Level Estimates of Large Firms' Weight and of the Debt-at-Risk

(Share of debt of large firms; share of debt at firms with EBIT-to-interest below 1 in 2016)

	Sample		System							
	ICR<1		Weight of Large Firms				ICR<1			
	Large	SME	Low Estimate	Central Estimate	Average Estimate	High Estimate	High Estimate	Central Estimate	Average Estimate	Low Estimate
China	23%	25%	38%	57%	67%	96%	24%	24%	24%	23%
Japan	3%	20%	42%	57%	65%	88%	13%	11%	9%	5%
United Kingdom	32%	38%	62%	62%	75%	89%	34%	34%	33%	32%
United States	15%	64%	40%	53%	70%	99%	44%	38%	30%	15%
France	15%	38%	34%	60%	63%	92%	30%	24%	23%	16%
Germany	21%	24%	55%	55%	73%	91%	22%	22%	22%	21%
Italy	19%	28%	27%	56%	46%	66%	25%	23%	23%	22%
Spain	21%	34%	38%	51%	56%	73%	29%	28%	27%	25%
Average	*19%*	*34%*	*42%*	*56%*	*64%*	*87%*	*28%*	*25%*	*24%*	*20%*

Sources: Bureau van Dijk Orbis; S&P Market Intelligence; WIND; and IMF staff calculations.

Scenario Analysis

Orbis's coverage is fairly good until 2016–17, while CIQ and WIND have nearly complete samples through 2018. Estimates for 2017–19 are made using the tools described below, based on: (1) historical and baseline GDP growth; and (2) a constant interest rate on debt through 2019.[28]

An adverse scenario is constructed to examine the sensitivity of debt-at-risk to an economic downturn. EBIT and interest are projected through 2021 at a firm level, while balance sheet items, such as assets, cash, and debt, are assumed to be constant. The adverse scenario is calibrated to emulate half the severity of the global financial crisis.

During the global financial crisis, GDP growth in these major economies declined, on average, by about 3 standard deviations. So, in the adverse scenario, GDP growth is assumed to decline by 1.4 standard deviations cumulatively in 2020–21. Table 2.6 shows GDP growth rates in the scenario by country.

[27] *Half* of total loans is picked in the presence of flat priors about the distribution of total loans by firm size. A more informed assessment would require a loan-level data from credit registries, which is beyond the scope of this analysis.

[28] The net changes in corporate bond yields between 2016/17 and 2019 are small (from +29 to -28 basis points). In addition, annual changes in corporate bond yields take from 5 to 14 years to be fully reflected in the interest expense, based on average maturities of major bond indices.

Online Annex Table 2.6. Adverse Scenario for GDP Growth

(Standard deviations in annual GDP growth rates; GDP growth in percent; decline in percentage points)

	Shock in Standard Deviations in 2020–21	GDP Growth in 2020	GDP Growth in 2021	Cumulative Decline from Baseline
China	1.4	4.6	3.1	4.1
France	1.4	0.2	-0.8	3.2
Germany	1.4	-0.9	-2.4	6.5
Italy	1.4	-1.5	-2.9	5.8
Japan	1.4	-0.5	-1.9	3.4
Spain	1.4	0.4	-1.4	4.6
United Kingdom	1.4	0.1	-1.1	4.0
United States	1.4	1.3	0.2	2.4

Sources: IMF *World Economic Outlook*; and IMF staff calculations.

The declines in EBIT are based on regressions of EBIT-to-assets and GDP growth by country, sector, and by firm size for each of the three databases. Table 2.7 shows that the declines in EBIT based on GDP regressions are, on aggregate, similar to but somewhat less severe than half the actual declines in EBIT during the GFC.

Online Annex Table 2.7. Adverse Scenario for EBIT: Modeled versus Historical GFC Impact

(Outcomes for 2021; 2017=1; quartiles across countries, firm sizes, and sectors)

	Orbis		CIQ		WIND	
	Based on:					
	Model	History	Model	History	Model	History
1st Quartile	0.88	0.88	0.75	0.59	0.76	0.60
2nd Quartile	0.92	0.91	0.85	0.77	0.80	0.75
3rd Quartile	0.94	0.94	0.91	0.89	0.86	0.80

Sources: Bureau van Dijk Orbis; S&P Market Intelligence; WIND; and IMF staff calculations.
Note: the modeled impact is based on GDP regressions and the assumption of GDP falling by 1.4 standard deviation (half the severity of the GFC). The historical impact is based on EBIT falling half-way to its GFC low.

The interest rate on debt for each firm is assumed to rise to half the level observed during the GFC. These outcomes are compared to the results from the corporate bond spread model for the United States. Table 2.8 shows that the increases in interest rates for large and medium firms are similar, on average, to the findings from the model, but the increase for small firms is greater than what the model implied. The latter finding is not surprising because the corporate spread model is developed for *aggregate* indices of investment-grade and speculative-grade bonds.

Online Annex Table 2.8. Adverse Scenario for Interest: Modeled versus Historical GFC Impact

(US firms; increase in the interest rate by 2021 in basis points)

	Orbis		CIQ	
	Based on:			
	Model	**History**	**Model**	**History**
Large	63	65	68	60
Medium	77	75	77	99
Small	101	54	67	136
All	*65*	*63*	*68*	*60*

Sources: Bureau van Dijk Orbis; S&P Market Intelligence; and IMF staff calculations.
Note: the modeled impact is based on the corporate spread model and the assumption of its components deteriorating to half of their GFC levels. The historical impact is based on the interest expense rising half-way to its GFC high.

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3. Technical Note on Investment Fund Stress Testing[29]

This note presents details on the methodology used for the liquidity stress scenario presented in Box 3.1.

Objectives: As highlighted in Box 3.1, the stress scenario aims to assess whether fixed-income funds could meet severe but plausible increases in redemption requests by disposing exclusively of liquid assets. The following steps were performed: (i) the volumes of liquid assets of individual funds were quantified using alternative liquidity concepts; (ii) the sizes of the funds' redemption shocks were calibrated following the procedure detailed below; (iii) for each fund and each liquidity concept, liquidity shortfalls were computed as the maximum of zero and the difference between the redemption shock calculated in (ii) and the liquidity buffers derived in (i); and (iv) two measures of aggregate liquidity shortfalls were computed (one aggregating the shortfalls across all funds and another one aggregating shortfalls across all those funds that had positive shortfalls). Intuitively, the average shortfall across all funds provides a quantification of the ex-ante liquidity risk investors accept by purchasing shares of fixed-income funds; whereas the average shortfall across all funds with positive shortfalls captures the ex-post risk of investors locked in shares of funds which turn out to suffer shortfalls when exposed to liquidity stress.

Data: A sample of 1,760 funds from 34 jurisdictions was selected on the basis of :(i) data availability; and (ii) a minimum size of $1 billion from the Morningstar Direct database. For this sample, the data items listed in the box to the right were collected for the time period from January 2000 to June 2019.

Monthly Data Series used:

- Fund sizes in home currency and in US dollars;
- Net redemptions (historical fund-level data);
- Fractions of funds' portfolios invested in debt by credit rating (AAA - unrated) in two versions: (i) reported by funds and (ii) calculated by Morningstar on the basis of individual securities' ratings;
- Funds' asset allocations including the positions in cash, bonds, equity and other assets;
- Funds' fixed income portfolios differentiated by position types, e.g., cash and cash equivalents, sovereign debt, corporate debt, municipal debt, securitized assets and derivatives; and
- Funds' positions in preferred stock, a senior form for equity, and agency mortgage-backed securities.

Data adjustments: Corporate debt positions are adjusted for preferred stock positions, which are considered equity. *Agency mortgage-backed securities* are removed from securitized assets and are used as separate portfolio components. The two types of rating quality data are merged into a single metric, by using the data calculated by Morningstar for all periods after December 2016, if available, and using the fund reported data in all other cases.

[29] This section was prepared by Frank Hespeler.

Liquidity shortfalls: Liquidity shortfalls are computed from redemption shocks and three alternative liquidity metrics: High-Quality Liquid Assets (HQLA), Alternative High-Quality Liquid Assets (AQLA), and narrow liquidity, which is the cash position of a fund. Redemption shocks are defined as the worst percentile of each fund's individual monthly net outflows observed over the period 2000 to 2019. Redemptions which exceed in absolute value 50 percent of the previous month's net asset value of the respective fund are dropped as they are considered to be statistical outliers, which means that they might be generated by erroneous data submission or extreme situations like fund closures. Individual fund liquidity shortfalls are aggregated across funds on an asset-weighted basis. Due to data availability constraints, all final metrics are converted to quarterly frequency.

High-Quality Liquid Assets: The computation of the HQLA proxy for liquidity buffers follows the Basle III principles for the calculation of the liquidity coverage ratio. In this concept, haircuts are used to model the fraction of assets that cannot be sold at short notice. These haircuts depend on the asset class and credit quality (Table 3.1). Corresponding haircuts are deducted from respective portfolio components, which are subsequently aggregated into the HQLA metric.

Online Annex Table 3.1. Basle III Liquidity Coverage Ratio Haircuts

<table>
<tr><th>Rating Grade</th><th>AAA</th><th>AA</th><th>A</th><th>BBB</th><th>BB</th><th>B</th><th>Below B</th><th>Unrated</th></tr>
<tr><td>Sovereign Debt</td><td>0</td><td>0</td><td>15</td><td>50</td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td>Corporate Debt</td><td>15</td><td>15</td><td>50</td><td>50</td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td>Equity</td><td colspan="8">50</td></tr>
<tr><td>Residential Mortgage</td><td>25</td><td>25</td><td colspan="6">100</td></tr>
<tr><td>Cash</td><td colspan="8">0</td></tr>
<tr><td>Municipal Debt</td><td>50</td><td>50</td><td>50</td><td>50</td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
</table>

Source: Bank for International Settlements.
Note: Based on high level principles.

Alternative High-Quality Liquid Assets: A fund may have more liquid assets on hand to meet redemption demand than is apparent from the HQLA measure. These additional liquid assets may, for example, be funded by short positions that are netted out in the HQLA measure. The AQLA measure corrects for this by balancing such positions against other (non-liquid) portfolio components. The measure excludes short positions in liquid assets that are used to finance long positions in other assets. It curtails, however, individual long positions in liquid assets exceeding the value of the entire portfolio, since excessive liquidity financing through short positions in illiquid assets seems unreasonable. The AQLA metric thereby provides a liquidity concept which allows the fund to maintain short positions during redemption stress as would be the case with credit lines. Hence it provides additional action space for liquidity management. AQLA is therefore a wider concept for liquidity than HQLA, as also illustrated by Fig 3.1.1 panel 1 in Box 3.1.

The adjustments used for the construction of the AQLA metric, described above, are implemented in turn, starting with short or excess long positions in the most liquid part of the portfolio and then through the less liquid parts of the portfolio in order. More formally, the adjusted portfolio components are computed as

$$\hat{x}_i = \begin{cases} x_i + \min(-x_i, \sum_{n\neq i} x_n) - \sum_{j=1}^{i-1} \max(\hat{x}_j - x_j, 0) & if \quad x_i < 0 \\ x_i & if \quad 0 \leq x_i \leq 1, \\ x_i + \min(0, \sum_{n\neq i} x_n) - \sum_{j=1}^{i-1} \min(\hat{x}_j - x_j, 0) & if \quad x_i > 1 \end{cases}$$

where $\hat{x}_i$ denotes the adjusted portfolio component (as a fraction of the entire portfolio), x_i is the unadjusted portfolio component and the indexes *n* and *i* denote the number of portfolio components and the liquidity rank of the specific component to be computed respectively.

The same methodology is used to clean the cash positions reported by the funds to generate the cash liquidity buffer used for the computation of the shortfall versus the narrower cash liquidity concept.

References

Bank for International Settlements. 2013. "Basel III: The Liquidity Coverage Ratio and Liquidity Risk Monitoring Tools." https://www.bis.org/publ/bcbs238.pdf.

4. THE SAMPLE OF EMERGING MARKET STATE-OWNED ENTERPRISES[30]

The analysis of State-Owned Enterprise (SOE) debt is based on a sample of large SOEs, which have a history of issuing US dollar denominated debt. This sample selection criterion was driven by the need to have a time series of ratings, prices and spreads for bonds issued by the SOEs as well as their sovereigns. Eighteen SOEs were thus selected for the analysis: CFE (Mexico), CNOOC (China), Codelco (Chile), DP World (Dubai), ENAP (Chile), Eskom (South Africa), Gazprom (Russia), KazMunayGas (Kazakhstan), Ooredoo (Qatar), Pemex (Mexico), Pertamina (Indonesia), Petrobras (Brazil), Petronas (Malaysia), PLN (Indonesia), Russia Railways (Russia), Sinopec (China), Taqa (Abu Dhabi) and YPF (Argentina).

The total amount of hard currency debt outstanding for these firms amounts to about $260 billion. That compares to $680 billion for all non-financial corporates included in the JP Morgan's CEMBI index. Some other large SOEs have issued significant amounts of hard currency debt in recent years, such as Aramco (Saudi Arabia) and ChemChina (China), but they were omitted from the analysis due to insufficient historical data. It should be noted that while two large Chinese SOEs were included in the analysis, China's broader SOE sector was not included in the analysis as most of the firms do not issue debt in offshore markets.

[30] This section was prepared by Jeffrey Williams.