S&P Global
Market Intelligence

Macro-Scenario Model

Conditioning Credit Risk Transitions on Macro-Economic Scenarios

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Overview

Risk assessment is the cornerstone of credit risk origination, valuation, surveillance, management and reporting processes regularly performed by risk practitioners at financial and non-financial corporations. At S&P Global Market Intelligence, the Credit Analytics suite allows you to assess credit risk of multiple counterparties in a holistic way, leveraging the speed, scalability and power of statistical models.

The assessment "philosophy" sits on a continuous spectrum between two stylized extremes:[1]

1. Point in Time (PiT): in which the model seeks to capture the dependence of risk on the business cycle, for example by using a daily-updated market-driven signal;[2] a consequence of such an approach is that during an economic downturn there is a general tendency of migration towards worse credit scores;
2. Through the Cycle (TtC): in which the model outputs a long-term and stable risk estimate, independent of the business cycle.[3]

A risk management "toolkit" cannot be considered complete without a tool that allows the analyst to explore how future economic scenarios may impact credit risk from a systematic point of view. There is, in fact, a well-known link between business cycle and credit cycle,[4] and ignoring this relationship can otherwise prove costly during periods of economic expansion or even fatal, during severe recessions, as the latest global financial crisis has bitterly reminded investors.

The Macro-Scenario (statistical) model represents the latest addition to the Credit Analytics suite, and enables risk managers and analysts to gauge how a firm's credit risk may change across both user-defined and pre-defined forward-looking scenarios, based on a set of macro-economic factors. The model can be used as a tool to support expected credit loss calculations required by the new accounting standards (IFRS9 and CECL[5]) that will become active globally, between 2018 and 2021.

Model Coverage and Features

The Macro-Scenario model has been trained on S&P Global Ratings' credit ratings[6] and leverages the historical statistical relationship observed between credit ratings' changes and corresponding macro-economic conditions to explore what future scenarios may bear.

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[1] Bank of England, Prudential Regulatory Authority: "Credit risk: internal ratings based approaches", (CP4/13 - March 2013).
[2] For example, S&P Global Market Intelligence's Probability of Default Model Market Signals.
[3] For example, S&P Global Market Intelligence's CreditModel™ 2.6.
[4] See, for example, "Credit Cycles and their role for Macro-Prudential Policy", November 2011 (European Banking Federation) available here: http://www.ebf-fbe.eu/uploads/28%20Nov-2011-EMAC.pdf.
[5] IFRS and CECL stand for International Financial Accounting Standard and Current Expected Credit Loss, respectively.
[6] S&P Global Ratings does not contribute to or participate in the creation of credit scores generated by S&P Global Market Intelligence.

Despite the majority of entities rated by S&P Global Ratings being high-revenue corporations, changes in the economic cycle are expected to affect credit risk of all firms in a consistent way, independent of their size. Thus, macro-scenario model inputs include both S&P Global Ratings' credit ratings and the outputs of Credit Analytics' fundamentals-based statistical models (CreditModel^{TM} 2.6 and PD Model Fundamentals).

We stress here that the macro-scenario model does not take into account company-specific characteristics, thus the model captures the *average tendency* of all companies with same credit-worthiness profile to transition to a different credit-worthiness level (or remain at the same level) under a given macro-economic condition.

Macroeconomic Factors and Macroeconomic Scenarios

Our model utilizes a sub-set of the list of factors that the banking industry regulators normally consider for stress-testing purposes; these variables were short-listed based on their predictive power, economic sense and the overall model performance.

Users can either leverage pre-defined scenarios, provided by the S&P Global Ratings Economists' team, or enter their own scenarios. In addition, users can toggle "on/off" an option (recession indicator) to simulate the severe impact of past economic recessions (e.g.: the 2008 global recession – for all modules – or the 2011 Sovereign debt crisis – only for the European Union model).

Model Scope, Country and Industry Coverage

The macro-scenario model inputs include S&P Global Ratings' credit ratings or CreditModel^{TM} 2.6 and PD Model Fundamentals outputs, covering financial and non-financial corporations within the industry sectors covered by those models and defined via the Primary Industry Classification Standard. The country coverage currently includes United States of America, Canada and the European Union plus the United Kingdom.[7] For more details about industry and country coverage, please refer to Appendix A and Appendix B, respectively.

Primary Model Outputs

The model's primary output is a credit score, expressed in lower-case letters,[8] representing the expected credit score that all companies with same current score will migrate to, within 1 year, based on the specified macro-economic scenario.

To simulate the evolution of the creditworthiness of a company over longer time horizons, users can run the model iteratively, using the credit score output from the previous step as input to the next iteration, with a new scenario.

As a quick alternative to running multiple scenarios over longer time horizons, users can leverage the term-structure provided (see below).

PD, Point-in-Time Adjustments and Term-Structure

The credit score is mapped to a TtC Probability of Default (PD), over 1 year and further adjusted in two ways:

- (Credit-Cycle Adjustment): by leveraging the historical default experience within S&P Global Ratings database to account for the *current point in time* within the credit cycle and
- (Market-Signal Adjustment): by considering the outputs from the market-driven PD model available within Credit Analytics (PD Model Market Signals) to incorporate a forward-looking *market view adjustment*.

[7] Here, European Union includes also the United Kingdom (UK), but the model was built to account for the case of "Brexit" (UK leaving the European Union), by employing a UK-specific factor.
[8] Lowercase nomenclature is used to differentiate S&P Global Market Intelligence PD credit model scores from the credit ratings issued by S&P Global Ratings.

The adjustments can be applied sequentially (first the Point-in-Time and then the forward-looking market view) or independent from each other.

The 1 year PD (with or without adjustments) is then extended to longer time horizons, using the historical shape of the term structure extracted from S&P Global Ratings default experience, for each different grade, and adjusted to ensure that the PD increases monotonically for worse credit scores and longer time horizons.

Stress-Testing and Reporting

Consistent with all our models, clients can utilize the Macro-Scenario model using pre-defined inputs or specifying their own scenarios, to perform a 'what-if' analysis, or even toggle a "recession switch" to simulate impacts similar to those of the most extreme economic downturns in the past 15 years.

Through its S&P Capital IQ platform, S&P Global Market Intelligence offers Desktop tools that cover both scoring and what-if analysis, where the impact of one or multiple macro-economic scenarios on the credit-worthiness of one or multiple companies can be assessed at once.

Aggregate Analysis and Surveillance dashboards allow the user to quickly compare creditworthiness and distribution of a portfolio of entities, covered by CreditModel, PD Model Fundamentals and PD Market Signals, monitor changes, and be notified via alerts if an entity breach a pre-set threshold.

For every analysis, reports can be generated with a comprehensive summary analysis, directly from the desktop or via Excel dynamically linking the analysis to PowerPoint via PresCenter™ to efficiently replicate credit memos or senior management presentations.

Integration with other S&P Capital IQ Platform Models

The Macro-Scenario can be used on a standalone basis, to assess expected changes of credit risk based on future macro-economic scenarios, or in conjunction with other S&P Global Market Intelligence's quantitative models, such as CreditModel, PD Model Fundamentals or LossStats™, to support calculation of expected credit losses for IFRS 9 and CECL purposes.

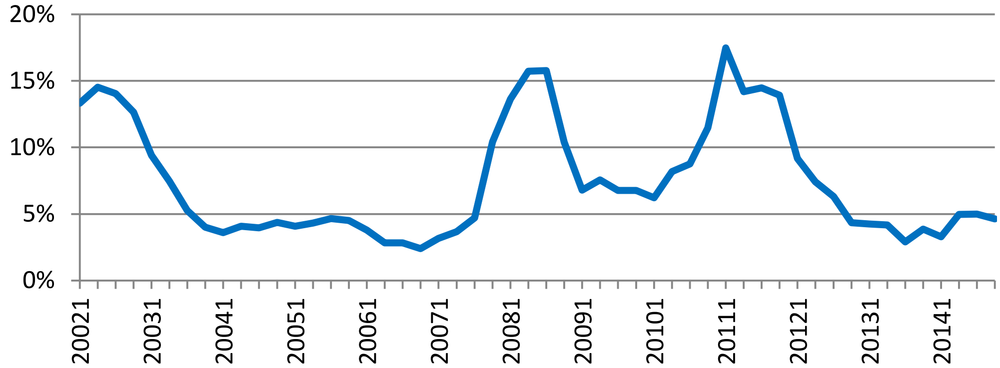
Macro-Scenario Model

A Tailored Framework

In response to the worst global recession experienced since last century, central banks in several developed countries have been adopting accommodative monetary policies to support local economies over a prolonged period of time; this has led to a stabilization or even a reduction of default rates historically observed in more recent years, and has thus contributed to a partial "breakdown" of the conventional relationship between business cycle and credit cycle.

Despite this, ratings at major rating agencies have maintained their dynamic behaviour, being only marginally influenced by the existence of this artificially benign credit cycle. Fig. 1 shows the fraction of European Union companies rated by S&P Global Ratings that have been downgraded by one rating "bucket" in the period 2002-2015.

Fig.1: Percent downgrades by one rating "bucket" (e.g. from AAA to AA+, AA or AA-) in Europe.



Source: S&P Global Ratings' issuer credit ratings (as of June 2016). For illustrative purposes only.

S&P Global Ratings' issuer credit ratings are long-term views of a company's credit-worthiness,[9] but the ratings criteria incorporate considerations around stressed macro-economic scenarios that companies with a certain rating must be able to sustain in order to be assigned that rating. Yet, this does not exclude an entity's rating downgrade under the stressed scenario. Therefore, ratings are not constant through time, and several downgrades can be seen across time, especially around recessionary periods.

Taking into account these empirical observations, at S&P Global Market Intelligence, we have decided to build a credit risk transition model conditioned on macro-economic scenarios, leveraging S&P Global Ratings' issuer credit ratings, rather than focusing only on default rates of low-default asset classes.

In the following section, we will describe in more detail the modelling processes we adopted.

Model Development Process

Trained on S&P Global Ratings and Macro-Economic Data Considered by Financial Institutions Regulators

We trained the Macro-Scenario model using more than 15 years of S&P Global Rating's historical rating transitions for financial and non-financial corporations (2000-2016) for US and Canada and (2002-2016) for European Union and UK. We used long-term local-currency issuer ratings rather than foreign-currency, due to their broader availability.[10] We considered a wide range of macro-economic factors (using quarterly frequency time-series), including the typical factors considered by banking regulators during the annual stress-testing exercise[11] and available in public websites.

[9] For definitions of S&P Global Ratings, see to: https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/504352.

[10] Corporations' local- and foreign-currency issuer credit ratings are expected to evolve in the same way in most cases.

[11] For example, the US Federal Reserve's Dodd-Frank Act Stress Testing exercise (see https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm).

Table 1: Model Development Sample Region Summary

Region[12]	Number of Observations for non-financial corporations	Number of Observations for financial corporations
United States of America	113357	61143
Canada	10298	3749
European Union and United Kingdom	29116	37770
Total	152771	102662

Source: S&P Global Market Intelligence. Data as of December 31st, 2016. For illustrative purposes only.

Vigorous Variable Selection Process

We calculated several versions of macro-economic factors (e.g.: the level, the year on year percentage change, etc.) and extended our analysis to several time lags (e.g.: no lag, 1 or 2 years lag), in order to investigate the most predictive variables for modelling purposes. We applied a vigorous, cutting-edge procedure for the variable selection process which helps to prescreen candidate inputs for modelling purposes. In order to select the final set of inputs and variables we used both statistical analysis and business judgment to weigh the following considerations:

Availability of Factors – All factors included in the model must be available on a consistent basis over time and their definition should remain stable. Some factors have a high predictive power but they may have been discontinued or their definition may have been changed (e.g.: VIX). While these factors may help boost a model's performance, such a model would be of little use if such variables are not available anymore or their definition keeps changing over time.

Correlation – Highly correlated factors do not provide additional insights and could distort model performance, due to multicollinearity effects. We use correlation analysis to identify and remove highly correlated variables.

Monotonicity – Each factor included in the model must have a clear directional impact (monotonicity) on the ratings change. For example, one expects the number of downgrades to increase and the overall default rate to increase when the Gross Domestic Product growth becomes negative.

Economic Sense – In order to capture the variety of factors that influence changes in creditworthiness, we referred to the list of factors that S&P Global Ratings' criteria consider when assessing a rating under a stress scenario.[13] In addition, we had extensive discussions with S&P Global Ratings Economists' team to corroborate our choices with expert judgement and overlay a sound macroeconomic intuition behind the final choice of model's factors.

Regional and Sector Segmentation

The model was separately trained for different regions/countries/industry sectors to take into account macroeconomic differences/similarities and the ratings evolution across the business cycle.

Due to the strong economic ties within the European Union (EU), the existence of a common market and a monetary union across many countries (e.g. the Eurozone), we chose EU-wide macro-economic variables, in line with those considered by the European Banking Authority in its EU-wide stress-testing exercise;[14] however, to reflect regional differences in the credit cycle of European economies at different development stages, to broadly align with the empirical observation that very rarely do Corporations' ratings assigned by S&P Global Ratings exceed that one of their Sovereign rating, and to be consistent with other Credit Analytics' statistical models that assess credit risk (e.g.: CreditModel™ 2.6 Corporates), we used 10 separate,

[12] Region or country.
[13] See for example S&P Global Ratings' "Understanding Standard & Poor's Rating Definitions" (Feb 23, 2017).
[14] See for example, "Adverse macro-financial scenario for the EBA 2016 EU-wide bank stress testing exercise", European Systemic Risk Board (29 January 2016).

region-specific, historical rating distributions (see “Sophisticated Methodology” section below).

Depending on ratings availability, industry sectors were trained by splitting into separate sub-models, or by consolidating all industries together and distinguishing them via industry-specific indicators.

Additional Features and Recession Indicator

Investment grade (IG) ratings have been historically less volatile than speculative grade (SG) ratings and our model incorporates an indicator to account for this difference.

Additionally, the model accommodates the impact of recent severe recessionary periods[15] on credit transitions by employing different prior distributions in stressed vs “normal” conditions. Users have the possibility to toggle a “button” and select “normal” or “stressed” case.

The S&P Global Market Intelligence tables below are all as of December 2017.

Table 2: Model Segmentation

Sub-Model	Selected Macro-Variables*	Further Segmentation
United States of America	Real GDP growth	24 *separate* industry sectors IG/SG indicator
	Unemployment rate change	
	BBB Corporates - 5 years Treasury yield change**	
	House Price Index Change	
	Oil Price***	
	Oil Price Change***	
	30 years Mortgage Rate – Prime Rate (change)	
	Dow-Jones Industrial Average Change	
Canada	Same as above, except for: - “BBB Corporates - 5 years Treasury yield change” is replaced with “10 years and 3 month Treasury yield spread”; - Oil Price Change is not included.	24 industry sectors (*indicators*) IG/SG indicator
European Union and United Kingdom (10 sub-regions)	EU STOXX Index change****	24 industry sectors (*indicators*) IG/SG indicator
	FTSE100 Index change****	
	EU28 Real GDP growth	
	EURO 10 Year Government Bond Yield – EURIBOR 3 Months Yield	

*Year on year percent change between next and current year. **Year on year percent change between current and previous year. ***Only for the energy sector. ****EU STOXX Index (FTSE100 Index) is used only for European Union countries excluding the United Kingdom (United Kingdom).
Source: S&P Global Market Intelligence (as of December 31st, 2016). For illustrative purposes only.

Sophisticated Methodology

S&P Global Market Intelligence’s model employs an advanced generalization of the logistic regressions, based on the family of Exponential Density Functions. It uses the long-term average distribution of all S&P Global Ratings’ credit ratings observed in the training dataset as a prior or “anchor distribution” for all the possibilities that may be seen at a future point-in-time, and modulates this distribution in proportion to how much the future macro-economic conditions improve or deteriorate to calculate the expected transition.

[15] The 2008 global recession or the 2011 sovereign-debt crisis in the European Union.

Our variable selection process considers both linear terms and terms of higher order, and selects the final variables according to k-fold Greedy Forward Approach, a widely-used statistical method that ensures a good fit out-of-sample and out-of-time.

The model uses various constraints, which avoid risk of model over-fitting without any loss of data and enable a more accurate estimation of the parameters and final output. For example, despite higher order terms were tested, they were not included in the final model, due to the limited model performance improvement.

The model maximizes the maximum likelihood function within a Maximum Expected Utility, adapted to the case of multi-state ratings, and uses comprehensive analysis, which include the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and out of sample performances, to limit the maximum number of variables that are included (model parsimony). This optimization process ensures the model exhibits greater stability and out-of-time performance. Moreover, monotonicity constraints are applied to ensure that the model produces outputs that follow economic intuition.

Benchmark Model

A common approach to estimate the impact of the business cycle on a company's credit-worthiness makes use of a "credit transition matrix approach" conditioned on a set of macro-economic factors.[16] The mathematical framework leverages an extension of the classical Merton model to the case of multiple thresholds, each delimiting a credit-worthiness category. As the economic cycle evolves, so do the thresholds that in turn characterize the probability of a credit transition within the matrix. This approach is usually implemented via a two-steps optimization process that initially identifies a credit cycle indicator for each credit transition matrix, and then regresses its systemic component against a number of macro-economic variables. A future macro-economic scenario translates in a different value of the credit cycle index, and thus in a different credit transition matrix.

Both approaches require a large dataset, but ours helps compensating for the potential lack of data and low default rates by calculating an overall expectation value across all possibilities for the future transition. Despite its wide-spread use, the common approach may be quite hard to calibrate properly, due to its 2-steps optimization process; our methodology, instead, requires a single optimization.

To benchmark our model vs the common approach, we replicated the common approach on all S&P Global Ratings' credit ratings assigned to US corporations between 2002 and 2015 and tested it vs our approach. As shown in Table 3, our model outperforms the "common approach", when looking at two commonly used performance measures (log-likelihood and mean squared error).

Table 3: Methodology Performance Comparison

Measure	"Common Approach"	S&P Global Market Intelligence's Methodology
Log-Likelihood[17]	-1.0258	-0.9882
Mean Squared Error	0.0046	0.0042

Source: S&P Global Market Intelligence (data as of December 31, 2016). For illustrative purposes only.

This confirms the power of our methodology, especially considering that our model was originally optimized on the first measure, while the "industry standard" was optimized by minimizing the mean squared error.

[16] See for example, B. Belkin & L. R. Forest, "A one-parameter representation of credit risk and transition matrices", J.P. Morgan's Credit Metrics® Monitor – page 46 (Third Quarter 1998), and J. Kim, "Conditioning the Transition Matrix", Risk Credit Risk Special Report, 37-40 (1999).

[17] The log-likelihood is a measure of the probability to find the modelled result within the training dataset; the higher the value, the better the model performs.

Model Performance

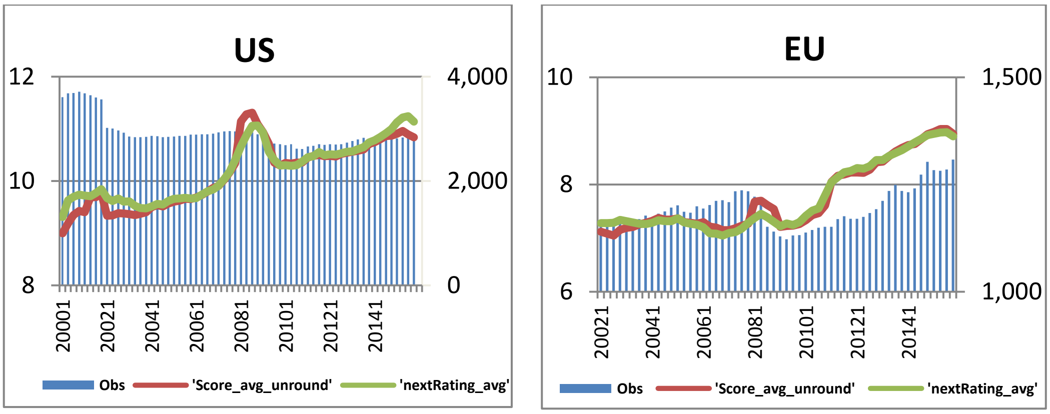
The Macro-Scenario model was trained on actual S&P Global Ratings' credit rating transitions between consecutive years, given the historical macro-economic factor changes observed in the corresponding period. The model's performance can be assessed in two ways, by looking at the overall model calibration and at the model's ability to replicate the observed rating transitions.

In the following discussion, the PiT adjustments are not applied, because we are interested in comparing the model outputs with the actual S&P Global Ratings.

Model Calibration

Fig. 2 below compares the average (weighted) score generated by the macro-scenario model for *next period* vs average (numerical) rating observed for companies rated by S&P Global Ratings in US (2000-2016) and in the European Union[18] (2002-2016) during *the corresponding next period*.

Figure 2: Model calibration in US and European Union (EU)



Source: S&P Global Market Intelligence. Data as of Dec, 31st 2016.

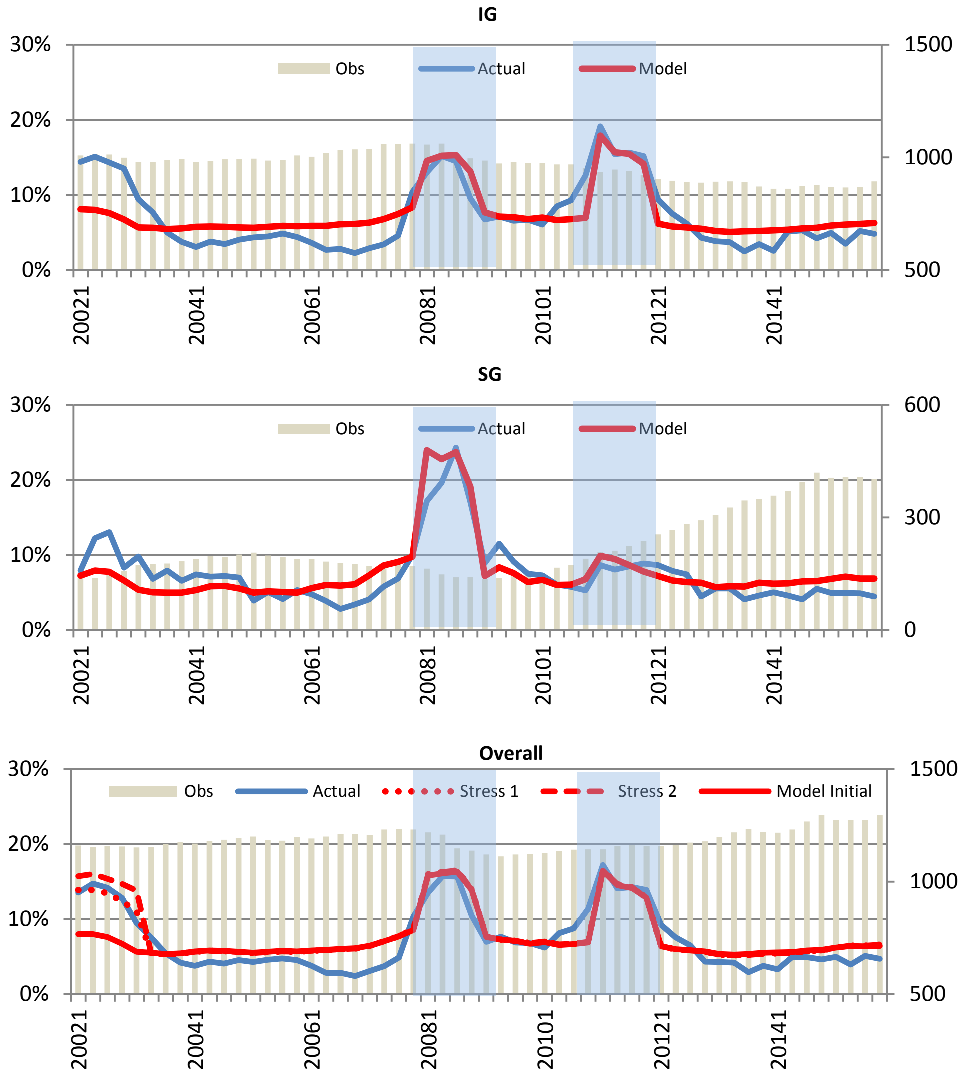
The average observed rating in both panels of Fig. 2 has progressively worsened between beginning of 2000's and now, with a pronounced, obvious "bump" during the recessionary period, in both US and European Union. The macro-scenario model nicely reproduces the *trend shape* and the *observed levels*, supporting the robustness of our methodology.[19]

[18] We also include the United Kingdom, because we are interested in the overall model calibration level.
[19] The average rating for US companies is worse than for European Union companies, since S&P Global Ratings includes many more SG ratings in US.

Model transitions

The following figure compares the percentage of downgrades[20] between year *t* and year *t+1* estimated via the macro-scenario model and the actual S&P Global Ratings' credit rating transitions observed for the same period, in the European Union. We show the results for the Investment Grade (IG) and Speculative Grade (SG) cases, as well as overall.

Figure 3: Rating Transition Downgrades by one "bucket" for European Union*



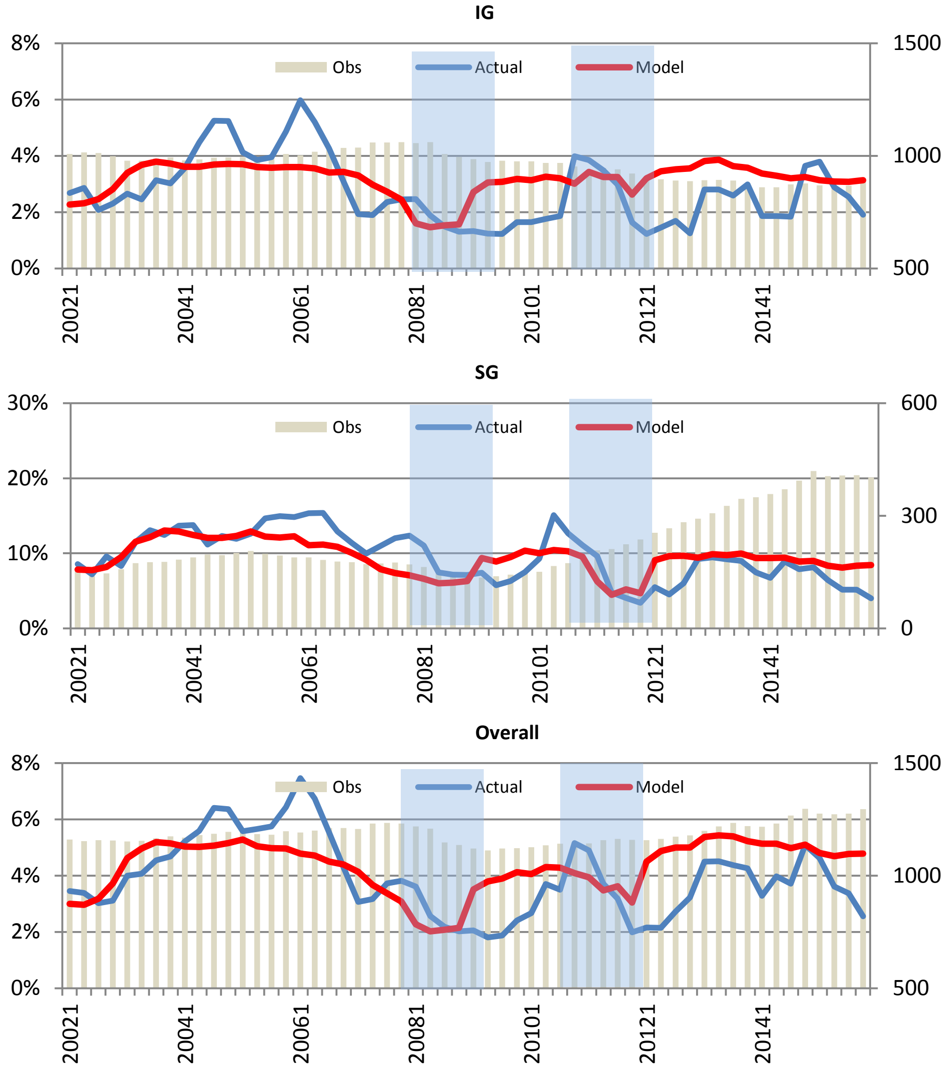
*For the purpose of this analysis, we included also UK, despite UK uses a country-specific macro-economic factor. Stress 1 and 2 refer to the 2008 and 2011 recession indicators, respectively. Source: S&P Global Market Intelligence. Data as December, 31st 2016.

In all cases, a good agreement is visible between modelled results and actual transitions, including the worst global recession period (areas shaded in cyan). For the period 2002-2003, we show the model outputs in the normal case (continuous red line), and when the recession indicator is activated for different stress periods within the European Union (dashed line for global recession and dotted line for the Sovereign debt crisis), thus confirming the value added by this indicator.

[20] In this context, a rating bucket includes a letter grade and its positive/negative notches; thus, a downgrade by one rating "bucket" involves any possible transition from (for instance) AA+, AA or AA- to A+, A or A-.

A reasonable agreement is also visible for the percentage of upgrades by 1 major rating "bucket" (see Fig. 4),[21] albeit characterized by a larger volatility, partly driven by the lower number of upgrades seen in past 15 years, and potentially related to a well-known "bias" detected by academic researchers:[22] after an initial downgrade, the odds of a further downgrade are higher; conversely, the odds of a further upgrade after an initial upgrade are pretty even.

Figure 4: Rating Transition Upgrades by one "bucket" for European Union*



*For the purpose of this analysis, we included also UK, despite UK uses a country-specific macro-economic factor. Source: S&P Global Market Intelligence. Data as of December, 31st 2016.

Similar results can be seen for US and Canada. Please, refer to the Appendix, for further information; a more detailed analysis is reported in the Technical Reference guide, available to existing clients upon request.

[21] Also in this case, we activated the recession indicator for the 2008 and 2011 recessionary periods.
[22] See for example: Edward I. Altman, "Estimating Default probabilities of Corporate Bonds over Various Investment Horizons" (March 2006), available at http://www.cfapubs.org/doi/pdf/10.2469/cp.v23.n1.3549.

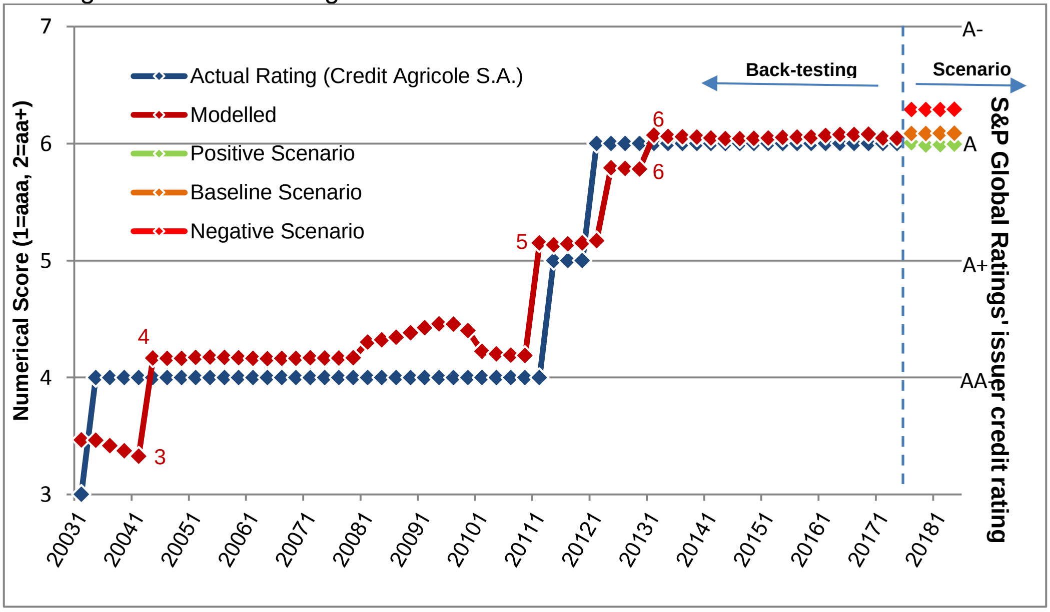
Case Study

Crédit Agricole S.A. is a French bank holding company, founded in 1894, providing retail, corporate, insurance, and investment banking products and services worldwide.[23]

By applying the actual macro-scenario at time *t* on the *previous year rating* within the macro-scenario model, we can backtest the statistical match between the model score expected for time *t* and the actual S&P Global Ratings' issuer rating, in the period 2013Q1-2017Q2. Figure 5 reports the scores as decimal numbers, prior to rounding.[24] In this example, the statistical Macro-Scenario model is very good at matching the actual S&P Global Rating, and nicely reproduces the evolution observed during the European Sovereign debt crisis.

However, it is important stressing that the macro-scenario model does not actually capture the idiosyncratic (or company-specific) risk component, thus in the eyes of the model all companies with same S&P Global Rating's credit rating as Crédit Agricole S.A.'s rating, will behave in the exact same way.

Figure 5: Comparison of macro-scenario model score expected vs actual S&P Global Rating's issuer credit rating at time t.



Source: S&P Global Market Intelligence. Data as November, 2017. For illustrative purposes only.

With this model, users can easily perform an analysis of the expected credit risk transition under different scenarios, for all companies with a given credit risk profile.

Figure 5 includes the outputs of the macro-economic scenario, when it is applied to estimate the expected credit risk transition on a quarterly frequency, from 2017Q3 to 2018Q2, under three arbitrary scenarios:[25]

- **Baseline scenario:** it is constructed from the rolling average over the previous 6 quarters;
- **Positive scenario:** it is constructed by from the baseline case, trebling all growth rates;
- **Negative scenario**: it is constructed from the rolling average over the previous 6 quarters, in the stressed period for EU28.[26]

[23] Source: S&P Capital IQ Platform, available at https://marketintelligence.spglobal.com .
[24] The rounded score is obtained with a simple mapping (e.g.: 1=aaa, 2= aa+, etc.)
[25] Users will be able to apply their own scenarios, or to leverage the S&P Global Ratings Economists' scenarios.

Under these artificial scenarios, all companies with an "a" score (as of 2017Q2) will remain at the same level over the next 4 quarters, but the associated 1 year TtC probability of default will be slightly different, because the 1 year TtC PD is obtained from the score, prior to rounding to the closest discrete level ("a" in this case).

Table 4: Mapped Probability of Default

PD (%)	2017Q3	2017Q4	2018Q1	2018Q2
Expected	0.056915%	0.056904%	0.056853%	0.056791%
Positive	0.055360%	0.054825%	0.054878%	0.055023%
Stress	0.062813%	0.062839%	0.062853%	0.062866%
Average	**0.058363%**	**0.058189%**	**0.058195%**	**0.058227%**

Source: S&P Global Market Intelligence (as of Nov, 2017). For illustrative purposes only.

In table 4 we also report the (simple) average PD that will turn useful for the next section.

A Potential Application to IFRS 9

The new IFRS 9 accounting standards[27] require all publicly listed companies (and most private banks) outside US and adhering to the IFRS to estimate *future* expected credit losses also on performing assets. The calculation needs to be performed over one-year time horizon or over the lifetime of the exposure, depending on whether there wasn't or there was significant credit risk deterioration since initial recognition, respectively. This is particularly important because this calculation directly impacts a firm's profit and loss statement.

The debtor's PD plays a crucial role in the calculation of future expected credit losses of loans and bonds and helps determining the time horizon over which the loss needs to be calculated (i.e. 1 year or lifetime).

The macro-scenario model offers an integrated and flexible tool that can be employed by corporations for the calculation of their debtors' *future* Point-in-Time PD and thus provides a solid base for the calculation of *future* expected credit losses, both over a 1 year time horizon and the lifetime of the credit exposure.[28]

In particular, according to IFRS 9:[29]

- "Any measurement of expected credit losses under IFRS 9 should reflect an *unbiased* and *probability-weighted* amount that is determined by evaluating the *range of possible outcomes* as well as incorporating the time value of money […]": a prudent (but not compulsory) approach for the calculation of the expected credit losses involves a weighted-average PD,[30] obtained by considering multiple macroeconomic scenarios, e.g. a baseline, a positive and a negative case, with weights defined according to the user's economic expectations.[31]

- "[…] the entity should consider *reasonable and supportable information about past events,* {and} *current conditions* […]": the macromodel comes equipped

[26] In addition, we switched on the "stress period" indicator.
[27] IFRS stands for International Financial Reporting Standard.
[28] S&P Global Market Intelligence's LossStats^{TM} model allows calculation of the loss given default of corporate loans and bonds.
[29] See, for example, International Accounting Standards Board- IASB (2014), "*IFRS 9 Financial Instruments",* July (www.ifrs.org).
[30] "IFRS 9 Forward-looking information and multiple scenarios" IFRS Foundation (July 2016 Webcast).
[31] We do not provide a tool for discounting purposes, but the process is quite straightforward, despite a bit laborious.

with a Point-in-Time adjustment on the PD that the user can toggle on/off. This is obtained by scaling the TtC PD by a non-linear coefficient that takes into account the *last year* historical default experience and the *long-term average* default experience in S&P Global Ratings' credit ratings database.

- In addition, the entity should consider "[…] reasonable and *supportable forecasts of future economic conditions* when measuring expected credit losses": in addition to enabling users to run multiple macro-economic scenarios, the model is able to incorporate a market-view adjustment. In this case, the (non-linear) scaling factor takes into account the average (benchmark) PD for companies in the same industry and country, calculated over last three months and over last year.

<u>One year vs lifetime calculation</u>

To establish whether the calculation needs to be performed over one year time horizon or the (remaining) lifetime of the exposure, users need to check whether the credit risk profile has deteriorated significantly since initial recognition. From this point of view, IFRS 9 is not prescriptive but several simplifications can be applied: for example,

- the credit risk on a financial instrument has not increased significantly since initial recognition if the financial instrument is determined to have low credit risk at the reporting date (eg: score in the investment grade);[32]
- the average PD over the (remaining) lifetime of the exposure *at the reporting date* has increased significantly vs the average PD over the lifetime at *initial recognition*; as an accepted practical expedient, one can compare the average 1 year PD at the reporting date and at initial recognition;
- there is, however, a (rebuttable) *presumption* that the credit risk on a financial asset has increased significantly since initial recognition when contractual payments are more than 30 days past due.

Let us see how to proceed in practice, using the previous case study as a starting point, and considering the case of a company with credit score "a" issuing a bond as of 2017Q3. At initial recognition (2017Q3), the average[33] 1 year PD over 3 scenarios (base line, positive and stressed) is reported in the last row of Table 4.

If we assume (for the sake of simplicity, in this case study) that the Point-in-Time adjustments do not modify the average 1 year TtC PD values considerably, there is no significant deterioration for the average 1 year PD at the next reporting period (2017Q4), thus the user can keep calculating expected credit losses over 1 year time horizon. Had the 1 year PD deteriorated significantly (for example, increasing by more than 60%), the user would need to use the lifetime PD (by leveraging provided term-structure, for example) and perform a full-blown calculation of the expected credit loss.[34]

Conclusion

We developed a macro-scenario model, utilizing a state-of-the-art statistical framework, trained on S&P Global Ratings' credit rating transitions observed over the past 15 years. Input factors are macro-economic scenario(s) for next year, either provided by the S&P Global Ratings Economists or user-defined. The model generates macro-economic conditioned credit scores, to perform scenario analysis, or

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[32] See for example: "Impairments of Greek Government Bonds under IAS39 and IFRS9: a Case Study", Guenther Gebhardt, (October 2015, Directorate General for Internal Policies), and references therein.
[33] We took a simple average, for simplicity.
[34] See for example: "Impairments of Greek Government Bonds under IAS39 and IFRS9: a Case Study", Guenther Gebhardt, (October 2015, Directorate General for Internal Policies).

IFRS 9 compliant PD values for the calculation of expected credit losses of credit exposures, such as bonds and loans.

APPENDIX A

Macro-Scenario Tool: Supported Industries (as of October 2017)

PICS	GICS Description
40101020	Aerospace & Defense
20302010	Airlines
25101010	Auto Parts & Equipment
25101020	Tires & Rubber
25102010	Automobile Manufacturers
25102020	Motorcycle Manufacturers
10101010	Oil & Gas Drilling
10101020	Oil & Gas Equipment & Services
10102010	Integrated Oil & Gas
10102020	Oil & Gas Exploration & Production
10102030	Oil & Gas Refining & Marketing
10102040	Oil & Gas Storage & Transportation
10102050	Coal & Consumable Fuels
45101010	Internet Software & Services
45102010	IT Consulting & Other Services
45102020	Data Processing & Outsourced Services
45103010	Application Software
45103020	Systems Software
45103030	Home Entertainment Software
45201010	Networking Equipment
45201020	Communications Equipment
45202010	Computer Hardware**
45202020	Computer Storage & Peripherals**
45202030	Technology Hardware, Storage & Peripherals
45203010	Electronic Equipment & Instruments
45203015	Electronic Components
45203020	Electronic Manufacturing Services
45203030	Technology Distributors
45204010	Office Electronics**
45205010	Semiconductor Equipment*
45205020	Semiconductors*
45301010	Semiconductor Equipment

45301020	Semiconductors
25301010	Casinos & Gaming
25301020	Hotels, Resorts & Cruise Lines
25301030	Leisure Facilities
25301040	Restaurants
20102010	Building Products
20103010	Construction & Engineering
20104010	Electrical Components & Equipment
20104020	Heavy Electrical Equipment
20105010	Industrial Conglomerates
20106010	Construction & Farm Machinery & Heavy Trucks
20106015	Agricultural & Farm Machinery
20106020	Industrial Machinery
20107010	Trading Companies & Distributors
25401010	Advertising
25401020	Broadcasting
25401025	Cable & Satellite
25401030	Movies & Entertainment
25401040	Publishing
35101010	Health Care Equipment
35101020	Health Care Supplies
35102010	Health Care Distributors
35102015	Health Care Services
35102020	Health Care Facilities
35102030	Managed Health Care
35103010	Health Care Technology
15101010	Commodity Chemicals
15101020	Diversified Chemicals
15101030	Fertilizers & Agricultural Chemicals
15101040	Industrial Gases
15101050	Specialty Chemicals
15103010	Metal & Glass Containers
15103020	Paper Packaging
35201010	Biotechnology
35202010	Pharmaceuticals
35203010	Life Sciences Tools & Services
25203010	Apparel, Accessories & Luxury Goods
25203020	Footwear
25203030	Textiles

30201010	Brewers
30201020	Distillers & Vintners
30201030	Soft Drinks
30202010	Agricultural Products
30202020	Meat Poultry & Fish
30202030	Packaged Foods & Meats
30203010	Tobacco
30301010	Household Products
30302010	Personal Products
25201010	Consumer Electronics
25201020	Home Furnishings
25201030	Homebuilding
25201040	Household Appliances
25201050	Housewares & Specialties
25202010	Leisure Products
25202020	Photographic Products**
25501010	Distributors
25502010	Catalog Retail
25502020	Internet Retail
25503010	Department Stores
25503020	General Merchandise Stores
25504010	Apparel Retail
25504020	Computer & Electronics Retail
25504030	Home Improvement Retail
25504040	Specialty Stores
25504050	Automotive Retail
25504060	Home furnishing Retail
30101010	Drug Retail
30101020	Food Distributors
30101030	Food Retail
30101040	Hypermarkets & Super Centers
15102010	Construction Materials
15105010	Forest Products
15105020	Paper Products
15104010	Aluminum
15104020	Diversified Metals & Mining
15104030	Gold
15104040	Precious Metals & Minerals
15104015	Silver
15104050	Steel

55101010	Electric Utilities
55102010	Gas Utilities
55103010	Multi-Utilities
55104010	Water Utilities
55105010	Independent Power Producers & Energy Traders
55105020	Renewable Electricity
50101010	Alternative Carriers
50101020	Integrated Telecommunication Services
50102010	Wireless Telecommunication Services
20201010	Commercial Printing
20201020	Data Processing Services
20201030	Diversified Commercial & Professional Services
20201040	Human Resource & Employment Services *
20201050	Environmental & Facilities Services
20201060	Office Services & Supplies
20201070	Diversified Support Services
20201080	Security & Alarm Services
20202010	Human Resource & Employment Services
20202020	Research & Consulting Services
25302010	Education Services
25302020	Specialized Consumer Services
20301010	Air Freight & Logistics
20303010	Marine
20304010	Railroads
20304020	Trucking
20305010	Airport Services
20305020	Highways & Rail tracks
20305030	Marine Ports & Services
40101010	Diversified Banks
40101015	Regional Banks
40102010	Thrifts & Mortgage Finance
40201020	Other Diversified Financial Services
40201030	Multi-Sector Holdings
40201040	Specialized Finance
40202010	Consumer Finance
40203010	Asset Management & Custody Banks
40203020	Investment Banking & Brokerage

40203030	Diversified Capital Markets
40301010	Insurance Brokers
40301020	Life & Health Insurance
40301030	Multi-line Insurance
40301040	Property & Casualty Insurance
40301050	Reinsurance
60101010	Diversified REITS
60101020	Industrial REITS
60101080	Specialized REITS
60101030	Hotel &Resort REITS
60101040	Office REITS
60101050	Health Care REITS
60101060	Residential REITS
60101070	Retail REITS
60101080	Specialized REITS
60102010	Diversified Real Estate Activities
60102020	Real Estate Operating Companies
60102030	Real Estate Development
60102040	Real Estate Services

APPENDIX B

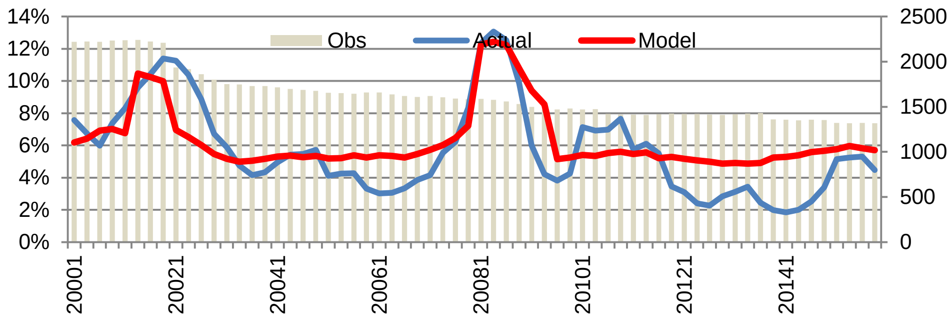
Macro-Scenario Tool: Country Coverage (as of October 2017)

	Country			
US Submodel	United States of America			
CA Submodel	Canada			
EU Submodel UK	United Kingdom			
EU Submodel	Austria	Estonia	Italy	Portugal
	Belgium	Finland	Latvia	Romania
	Bulgaria	France	Lithuania	Slovakia
	Croatia	Germany	Luxembourg	Slovak Republic
	Cyprus	Greece	Malta	Slovenia
	Czech Republic	Hungary	Netherlands	Spain
	Denmark	Ireland	Poland	Sweden

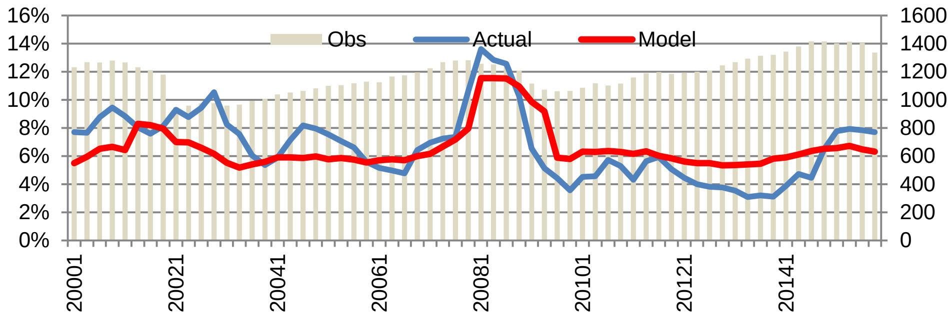
APPENDIX C

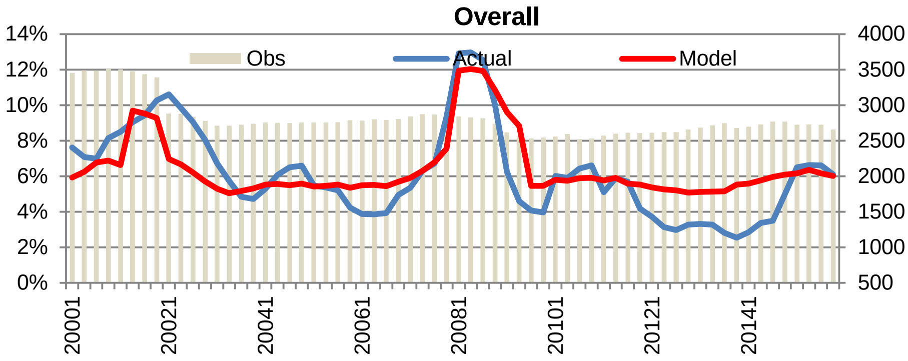
Figure 4: US Submodel Transition Performance
Panel A: Downgrade by 1 Bucket

IG

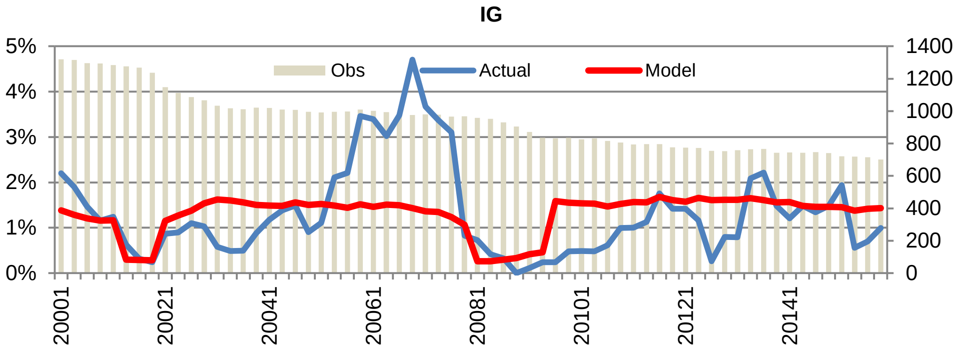


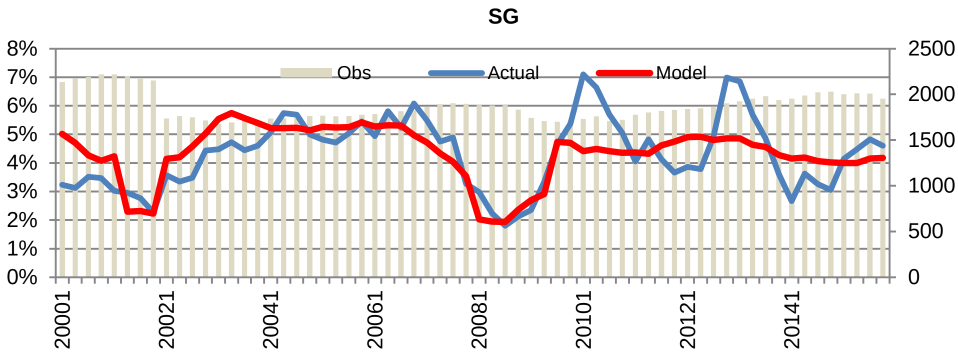
SG





Panel C: Upgrade by 1 Bucket





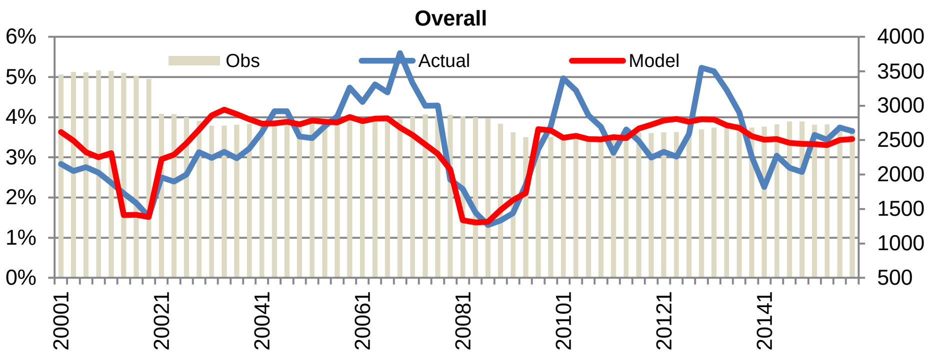
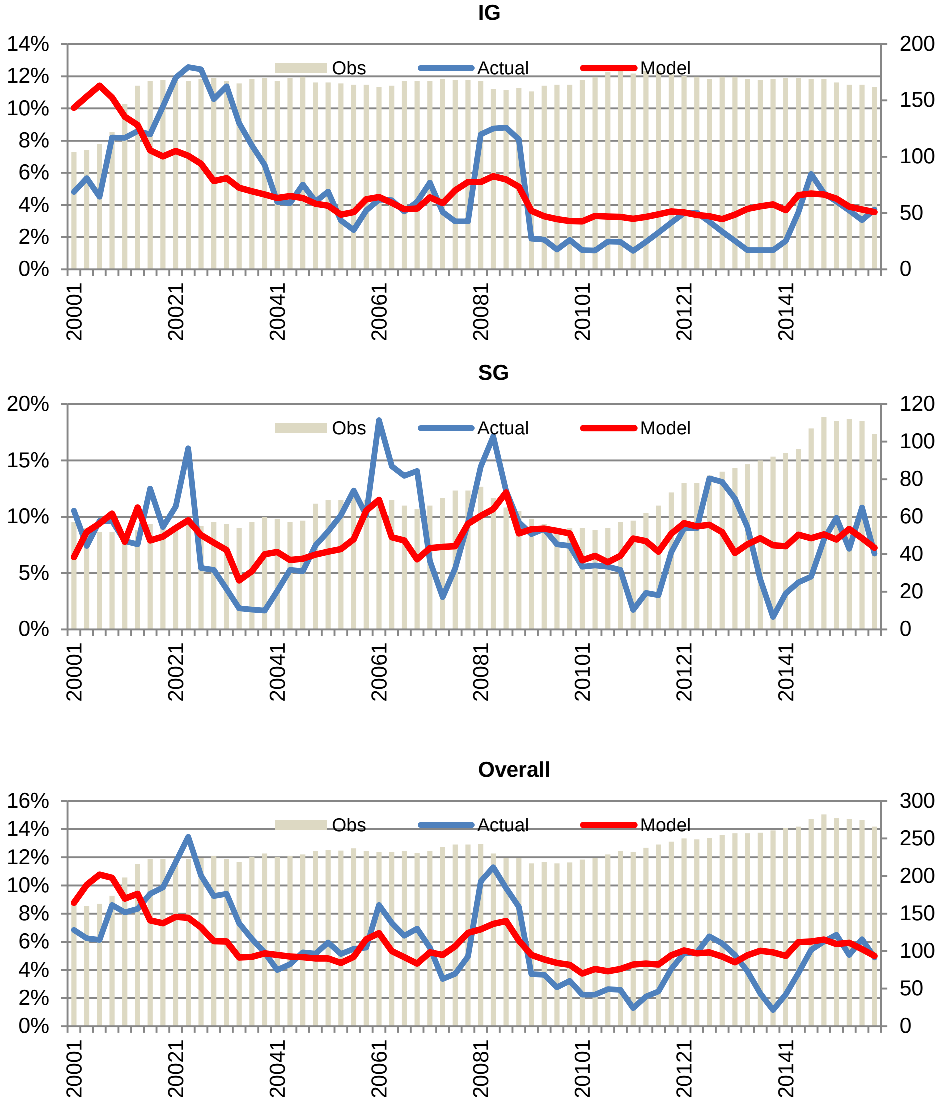
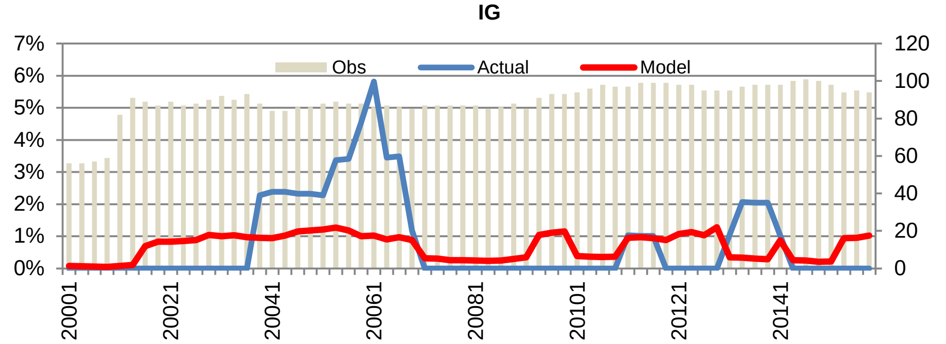


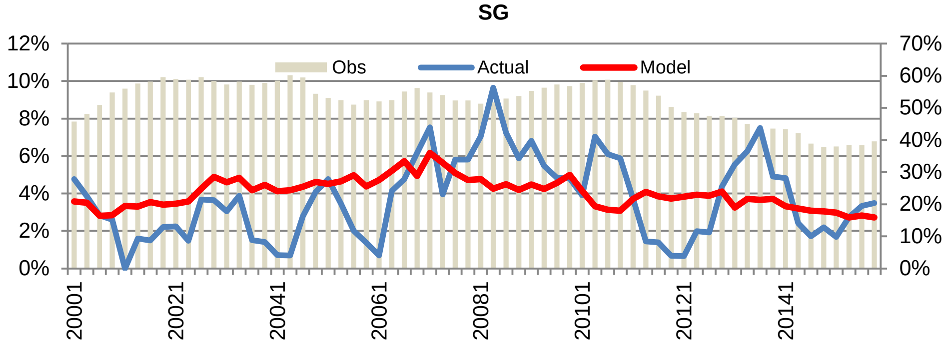
Figure 5: CA Submodel Transition Performance

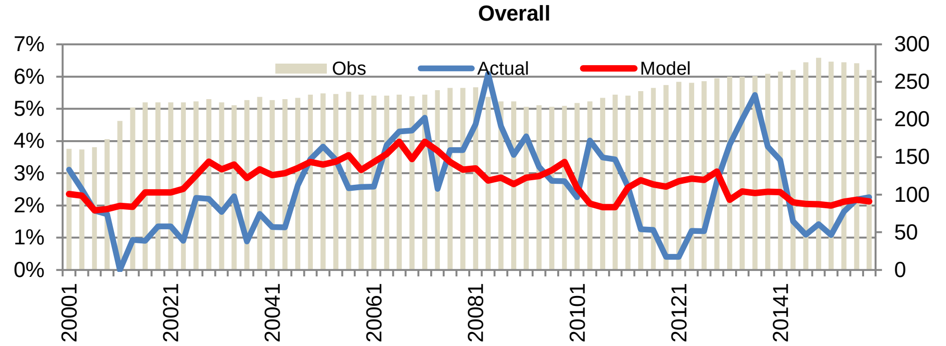
Panel A: Downgrade by 1 Bucket



Panel C: Upgrade by 1 Bucket







Source: S&P Global Market Intelligence. Data as of December 31st, 2016. For illustrative purposes only.

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