Fundamental Credit Analysis through Dynamical Modeling and Simulation of the Balance Sheet: Applications to Chinese Real Estate Developers

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10 April 2022

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Abstract

Fundamental credit analysis is widely performed by fixed income analysts and financial institutions to assess the credit risk of individual companies based on their financial data, notably the financial statements reported by the companies. Yet, the conventional analysis has not developed a computational method to forecast, directly from a company's financial statements, the default probability, the recovery rate, and ultimately the fundamental valuation of a company's credit risk in terms of credit spreads to risk-free rate. This paper introduces a generalizable approach to achieve these goals by implementing fundamental credit analysis in dynamical models. When combined with Monte-Carlo simulation, the current methodology naturally combines several novel features in the same forecast algorithm: 1. integrating default (defined as the state of negative cash) and recovery rate (under liquidation scenario) through the same defaulted balance sheet, 2. valuing the corporate real options manifested as planning in the amount of borrowing and expenditure, 3. embedding macro-economic and macro-financing conditions, and 4. forecasting the joint default risk of multiple companies. The method is applied to the Chinese real estate industry to forecast for several listed developers their forward default probabilities and associated recovery rates, and the fair-value par coupon curves of senior unsecured debt, using as inputs 6-8 years of their annual financial statements with 2020 as the latest. The results show both agreements and disagreements with the market-traded credit spreads at early April 2021, the time of these forecasts. The models forecasted much wider than market spreads on the big three developers, particularly pricing Evergrande in highly distressed levels. After setting up additional generic industry models, the current methodology is capable of computing default risk and debt valuation on large-scale of companies based on their historical financial statements.

Background

Fundamental credit analysis has been widely practiced by credit investors as well as lending institutions. The fundamental financial data of a company refers to the data contained in a company's financial reports, particularly the four financial statements and the notes to the statements. Credit analysts examine the data and disclosures in these statements in great granularity to assess a company's credit strength and default risk.

Despite of the detailed and comprehensive analysis performed, fundamental credit analysts cannot so far reach the ultimate goal - a fundamental-based valuation of a company's bonds or loans, because such valuation requires the forecast of a company's forward curve of probability of default and recovery rate of debt in each seniority class.

Many methods have been utilized to connect fundamental company data to the default risk quantitatively, which all involve defining certain financial metrics based on company fundamentals with the goal that companies categorized under such metrics show historically different levels of default rate at the category level. Credit rating is the most widely utilized categorization scheme due to their statutory status, but due to the ad hoc nature of any given metrics, there is no unified methodology among the practitioners, and many analysts and commercial companies develop their own metrics and mapping to historically guided default rates.

Despite of their usefulness, the financial metrics methods have many limitations. Because they are mapped to historical data, the forecasts they produce are fundamentally backward-looking and require static assumptions on the default rate. The grouping of companies into categories also take away much of the granular information regarding individual companies, making the forecasts unspecific to any single company.

These limitations stand as long as the approaches focus on modeling the patterns of the observed default rate as opposed to the underlying cause of default. In reality, default occurs simply when a company runs out of cash. It seems straightforward then that the key to modeling default risk is to model the change of cash in a company.

Such step has not been accomplished and there is a good reason – cash is the most unpredictable financial variable of a company because it interacts with every other financial variable involved in a company’s operation and financing. Cash level changes whenever a company buys, processes, or sells inventory, raises, or redeems debt, sells, or buys back shares, creates, or pays down payables, etc. In other words, cash cannot be modelled alone. Instead, all the financial items, in fact the entire balance sheet, must be modelled as a whole, as a multi-dimensional interactive system.

A pre-requisite for modeling such multi-dimensional interactive system is a good grasp of financial accounting and financial statements, which all financial analysts have been trained to do. However, the analysts are not trained to model dynamically the changes reflected in the financial statements - breaking down the reported changes into connected sequence of intermediary steps and discover the patterns in these underlying changes.

Contrary to fundamental credit analysis, the mathematical fields have produced a great amount of work on default modeling by radically simplifying a company's balance sheet. The structural models, a long lineage of work that began with Merton (Merton, 1974; Afika, Arad, & Galilb, January 2016; Zhou, 1997), compresses the entire balance sheet into a single variable – the value of a company’s total asset, while assuming the debt level to be fixed. The simplification avoids the need for financial accounting and financial statements in default modeling, but also in my view diminishes the usefulness of the model in practical applications.

The criterion of default in structural models – that the total asset value falls below the fixed debt level - is plainly wrong for the vast majority of non-financial companies. Certain regulated financial institutions may be declared insolvent when asset value falls below liability value, but non-financial corporations do not mark to market their total assets, and neither will they default because of it. The cause of a company’s default is negative cash, not negative equity. But another fundamental limitation all the structural models share is they cannot incorporate a fundamental symmetry of the financial dynamics.

A company’s financial state adheres to a fundamental constraint, vis-a-vis symmetry, at all times - the sum of total assets must equal to the sum of total liabilities. Analogous to a physical system, the symmetry of the balance sheet corresponds to a conservation law – the conservation of wealth, defined as the total shareholders’ equity. Here, conservation does not mean strict constancy, just like in the conservation laws of physical system, but rather the “difficulty” in creating wealth. For non-trivial dynamics that reflects this symmetry, minimally two dimensions of change, one in asset and one in liability, are needed. For an example of such a minimal model that is analytically solvable, see (Xu, 2023).

Fundamental credit analysis often extends from individual companies into the interactions between companies, and between companies and exogenous macro-conditions such as the economic growth rate and credit supply condition. However, without the ability to evaluate quantitively the default risk of individual companies, the fundamental credit analysis also falls short in assessing the risk of joint defaults or default contagions.

In summary, granularity is the key character of fundamental analysis, but granularity has also historically made the analysis unquantifiable and ungeneralizable. One strong attraction of quantitative models to the investment community is their ability to be applied to a large number of companies in standardized algorithms that produce results within feasible timeframe. The methodology in this paper and its demonstration in a complex industry, the Chinese real estate industry, show that granularity can equally lead to quantitative and generalizable algorithm that can compute the default risks and debt valuations automatically for vast majority of the companies with financial statements as the key inputs.

Methodology

The current methodology provides a way to implement fundamental credit analysis in quantitative dynamical models. The model utilizes the fundamental financial data of a company just as fundamental analysis does. The difference is that the current methodology allows the transformation of the data into dynamics such that the model can reproduce a company's historical financials and generate the possible paths of the future financials.

The methodology introduced in this paper is numerical in nature as opposed to analytical. Unlike the structural models but like any fundamental analysis, the current methodology requires substantial industry knowledge for modelling specific companies.

Balance sheet

Balance sheet is the central object to model in the current methodology. The modelled balance sheet corresponds to but is more complicated than the balance sheet reported in the financial statement. The actual number and the types of balance sheet fields chosen in a model depend on the specific industry and the modeler's objective to granularity. A general rule is to include fields that are necessary to explain the key changes reflected in a company's financial statements.

The model pre-defines each type of balance sheet field with their specific features and actions. The pre-defined fields include cash, loans, inventory, capacity, receivables, investments, payables, debt, deferred revenues, equity, and etc.

Goods and service companies

Within the current approach, all industries are divided into two fundamental types – one that sells goods and one that sells services, modelled with two special asset fields – inventory and capacity. Inventory corresponds to all sellable goods - foods, houses, chemicals, cars, etc, while capacity corresponds to the capability that can be rendered as a service - hotel rooms, airplanes, rental cars, etc.

The fundamental balance sheet restrictions

Two restrictions, or symmetries, are imposed on the balance sheet at all times.

1. With the exception of the equity field, the value of all balance sheet fields cannot be negative.
2. The sum of all asset book values equal to the sum of all liability book values.

The first requirement is a basic reality in the business world – you cannot deliver what you do not have. While the second requirement provides the principle that wealth is "difficult" to create. Together, the two restrictions limit the changes permissible to the balance sheet, which leads to the predictive power of the generated forecasts. The requirement of non-negative value also leads to the definition of default - when cash becomes negative following an elementary action.

Elementary actions

A key goal of financial modeling is to understand the changes reflected in a company's financial statements. This may seem to be an impossible task given the great number of fields contained in all four financial statements each year. Fundamental credit analysis normally manages the complexity by focusing on isolated metrics extracted from the financial data (S&P Global Rating, 2019; Ohlson, 1980; Altman, 1968). These approaches cannot capture in their forecasts the fundamental principles that can only be reflected when all the balance sheet fields are considered.

The current approach manages the complexity in a different way. A key realization is that the complicated changes reflected in a company's financial statement is the result of compounding many elementary changes, called actions hereafter. Each elementary action changes only a few fields on the balance sheet but represents a basic action that companies in all industries execute in conducting operation and financing. A finite set of fundamental actions are pre-defined in the current methodology. Critically, each action preserves the two fundamental restrictions of the balance sheet.

Model and calibration

A financial model in the current approach is a selection of ordered sequence of elementary actions. Given an initial balance sheet, the sequence of actions applied repetitively produces not only the new balance sheet over time, but also the income statement, as income and cost are generated by specific actions predefined in the model, and the flows of all balance sheet fields including cash. The exact outcome of an action is determined by the intensities of the action - the values of the parameters contained in the action. A financial model is calibrated if it solves the values of all the action parameters in the model such that the model reproduces the financial statements over a period of time from the initial financial statement of such period.

Forecasting by simulation

A calibrated model then generates the future balance sheet, income statement and the flows of all balance sheet fields from the same source of actions once the future values of the action parameters are given. The action values are forecasted through simulation in three different ways.

Random. Random parameters are variables a company cannot control or plan completely, such as the sales ratio of the current inventory. They typically follow normal distributions derived from their historical data.

Planned. Companies do plan many of their actions - the amount of inventory to buy, the amount of new debt to borrow, etc. based on the information they can observe in order to achieve certain financial goals. These optimized action values are computed in the simulation under a set of pre-defined goals such as avoidance of default and/or a growth target. A planned action value is chosen at each time step from a range of possible values by comparing the forecasts made, using the same company model, under each possible value and the realized random action values.

Bounded. Bounded parameters are either random or planned but their final values are limited by boundary conditions shared across companies. For example, a credit supply condition can be applied as an upper bound of annual growth rate of debt, normally per given level of existing debt leverage, and an overall market growth rate can be set as the upper bound on the annual sales growth rate of all companies in the market. Boundary conditions are exogenous to a company's financial data and are derived from historical data from an entire sector or market. The boundaries may be random themselves and may be changed dynamically by the financial outcome of the companies.

Default, recovery rate and fair-value par coupon curve

Probability of default

Along each simulation path, which consists of discrete time steps typically representing annual periods, the model produces the balance sheet and income statement following each action at each time step. If cash becomes negative following an action, the company defaults and the path terminates. The default probability of a time period is the ratio of defaulted paths in the period over the number of paths at the beginning of the period.

Recovery rates of different liability classes

Recovery rate is computed from the defaulted balance sheet through a liquidation scenario. The recovery rate of each liability field is determined by the assumed asset liquidation prices and the seniority of the liability field.

Fair-value par coupon curve

The default probabilities and associated recovery rates lead to fair-value par coupon curve of a company's debt. For each maturity date, a fair-value par coupon rate is the coupon that produces par expected net present value of a company's debt after realizing all default losses and recoveries and discounting all cash flows at the risk-free discount rates.

Joint default risk of multiple companies

Multiple companies can be simulated simultaneously with correlated random action values and synched boundary conditions, generating the distribution of relative default timing between the companies and the probability of default clustering. The current methodology allows a fully bottom-up approach in computing portfolio risk.

Application to Chinese real estate developers

The current methodology is applied to Chinese real estate companies to demonstrate its practical feasibility. A generic model is built for the real estate development industry in China, which is calibrated to 9 public companies, using 6-9 years of historical annual statements, up to 2020. The simulation forecast is conducted on the key action parameters based on the industry characteristics. In the forecast, credit boundary conditions of maximal annual debt and payable growth rates as a function of a company's debt-to-equity ratio are defined exogenously and are applied to all companies. The detailed model settings are provided at the end of the paper.

Unique industry characters in China

The Chinese Real Estate Industry is the largest non-financial issuer in Asia of USD corporate bonds. Based on the JPMorgan JACI index as of the end of 2020, Chinese developers have 570 billion USD bonds outstanding, a 10% of all USD bonds issued in Asia. A unique character of the real estate development in China versus that in other countries is the presale of uncompleted development projects at full value to buyers. Generally speaking, a residential project takes two years to complete while a developer normally presells the project units one year after land purchase. The developers can use the presale proceeds as new capital for land acquisition as bank loans are generally forbidden in China for such purpose.

Another unique character of the Chinese property developers is the importance of payables. Payables are normally not considered a key liability by financial analysts and are often treated as short-term liability with predictable, typically less than a year, turnover rate. This is not the case in China. For the three largest developers (Evergrande, Country Garden and Vanke), the amounts of total payables including amounts due to related parties have exceeded the level of debt in recent years. As indicated by models calibrated to the historical financial statements, payables have become an importance class of financing avenue for Chinese developers and their paydown speed, which has significantly slowed in recent years, is a strong determinant of a company's liquidity and default risk.

Results

The forecasting was performed over discrete annual time steps. It is worth noting that the forecasts have assumed no new equity raising, and no new MTM gain or loss on investments.

The forecasted annual default probability of each company over a 10-year period are provided in Table 6 at the end of the paper.

Given the number of paths N at the beginning of each time period, default probability within the period can change only in the increment of $1/N$. This is the precision limit of the forecast. The precision limits for the forecasts of annual default probability are provided in Table 7. The higher the initial default probabilities are for a company, the less precise the later forecasts become as fewer paths remaining in the simulation.

The average recovery rates, from all defaults occurred within the same period, are provided in Table 9 for senior unsecured debt of each company. The assumed percentage of secured debt among senior debt for each company is provided in the same table.

Table 10 provides the fundamentally valued par-coupon curves of senior unsecured debt for each company.

In the current approach, credit and equity analysis are unified in the forecast as equity is just another liability field in the balance sheet, one that is the lowest ranked and hence mostly having zero recovery value in the case of default. The expected forward levels of shareholder's equity can be computed from the same simulation outcomes, and they are provided in Table 11 for all the companies studied.

In the current forecasts, the 9 companies are simulated simultaneously with interlinked paths. The random action values for the 9 companies are generated with their historical correlation coefficients and the same credit boundary functions are applied to all companies at every time step. The interlinked paths produce the relative default timings for the companies across the group. Table 12 provides the distribution of maximal number of companies defaulting in the same year over 5 and 10-year horizon. The result shows significant tail risk of having more than half of the group (≥5 companies) defaulting in the same year - 10% of the scenarios over 5 years and 12% of the scenarios over 10 years.

Discussions

Comparison to the market prices of company bonds – market bias to large companies

The model-implied par coupon rates of each company's senior unsecured bonds in 2, 5, and 10-year maturities are compared below (Table 1) with the available market prices on the company's USD bonds, measured in spreads over Treasury yields, as of early April 2021 around the time when the companies' 2020 annual statements were published. For Longfor and Agile, the model-implied spreads are much tighter than the market levels, while for Vanke, Country Garden, and Evergrande the model-implied spreads are much wider than the market levels. In the case of Shimao, Greentown, Yuzhou and Sunac, the model results broadly agree with the market, although for Yuzhou and Sunac, the model projects a steeper shape of the spread curve than the market.

The results suggest that market has a positive bias to large companies versus small companies compared to the fundamentally valuations. The bias can be based on the belief that creditors hold the same preference toward large companies versus small companies.

At the time of these results, Evergrande has not defaulted. In agreement with the market-traded spreads, the model has singled out Evergrande as the riskiest company within the group. However, the model projects a much wider fair value spread than the market was pricing in at the time.

Table 1. Comparison of model-derived versus market-traded bond credit spreads

Company	Par coupon spread over Treasury (bps), of unsecured debt			Market traded bond credit spread (bps), May 2021		
	2yr	5yr	10yr	2yr	5yr	10yr
Longfor	23	22	16	130	150	160
Vanke	229	662	824	130	150	170
Co Garden	1364	1307	866	350	360	290
Shimao	155	279	270	360	300	250
Agile	0	161	175	450		
Greentown	381	860	1140	440		
Yuzhou	336	747	1606	480	550	
Sunac	204	816	924	550	550	
Evergrande	2166	3215	3416	1300	1300	

Implied mid to long-term credit ratings using cumulative default rate – Caa ratings in Yuzhou and Evergrande, but also significantly lower ratings in others.

The model-forecasted cumulative default probability of each company over each time period can be compared to the historical cumulative default rates of each rating given by the rating agencies, and an equivalent rating can be implied accordingly. Table 2 below shows the implied rating based on Moody's historical cumulative default rates during 1970-2005 (Moody's Investors Service, 2006). The actual ratings of the companies as of April 2021 are provided in the last column.

If a company's mid to long-term rating is naively the average of the implied ratings from year 5 to year 10 in Table 2, then Yuzhou, Evergrande, and Greentown would be rated in Caa, and both Vanke and Country Garden would be rated in B, all significantly lower than their actual ratings at the time. Both Yuzhou and Evergrande have defaulted, but Greentown has not. The implied ratings of the remaining four companies agree with the actual ratings.

Table 2. Model-implied ratings corresponding to Moody's historical cumulative default rates

Company	Years									Rating 4/2021
	2	3	4	5	6	7	8	9	10	
Longfor	Baa	Baa	Baa	Baa	Baa	Baa	Baa	Baa	Baa	**Baa2**
Vanke	Ba	B	B	B	B	B	B	Caa-C	Caa-C	**Baa2**
Co Garden	B	B	B	B	B	B	B	B	B	**Baa3**
Shimao	Ba	Ba	Ba	Ba	Ba	Ba	Ba	Ba	Ba	**BB#**
Agile	Aaa	Baa	Ba	Ba	Ba	Ba	Ba	Ba	Ba	**Ba3**
Greentown	Ba	B	B	B	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	**Ba3**
Yuzhou	Ba	B	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	**B1**
Sunac	Ba	Ba	Ba	B	B	B	B	B	B	**B1**
Evergrande	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	Caa-C	**B2**

Rating by S&P

Corporate real options are quantifiable with substantial value

In the forecasts, if the planned action values - amount of new debt, amount of inventory and payables paydown rates - are simulated randomly instead, the default risk is elevated substantially, as the example of Shimao below shows (Table 3).

Table 3. Default probabilities under fully random simulation versus simulation with embedded planning.

	Shimao annual default probability year 1-10									
	1	2	3	4	5	6	7	8	9	10

Random	0%	23%	32.5%	30.8%	27.8%	34.6%	53.9%	37.5%	0%	25%
Planned	0%	5%	5.3%	8.9%	8.5%	5.3%	5.6%	10.4%	1.7%	3.4%

In fair-value par coupon terms, the corporate planning amounts to 300 bps to 400 bps reduction along the curve.

Credit boundary condition is a strong determinant of default

Lowering the upper bounds on the growth rate of debt and payables can raise the probability of default significantly, although the effect can be uneven to different companies. The following example of Yuzhou (Table 4) shows the dramatic difference of the default forecast under neutral versus severe credit conditions.

Further simulations show that in the extreme cases, every company in the group can evade default forever if there is no upper bound to debt growth, and every company defaults quickly if borrowing is shut down suddenly and completely.

The credit boundary condition in this application is a random distribution of the upper bound of debt growth rate for each level of debt-to-equity ratio. Currently, the distribution is exogenously derived from historical data of debt growth rates. In principle the credit condition to each company is determined by its lending parties based on their assessment of the company's credit risk. Potentially, the current models can also be used to simulate this determination process.

Table 4. Default probability under different constant levels of credit boundary condition

Credit condition	**Yuzhou annual default probability year 1-10**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Neutral (50%)	0%	0%	20%	0%	13%	23%	15%	17%	16%	16%
Tight (20%)	0%	49%	64%	38%	63%	100%				

Sharing of credit condition increases default clustering among the group

The simulations on the 9 companies are conducted with synchronized credit boundary conditions and correlated random action values over 100 scenarios. Table 12 summarizes the distribution among the scenarios of maximal number of companies defaulting in the same year over 5 and 10-year horizon. If the simulation of each company is run with independently random boundary conditions, the default clustering is significantly reduced (Table 5).

Table 5. Distribution of different levels of default clustering under independent and synchronized credit boundary conditions

	Maximal number of companies defaulted in the same year over 10-year horizon									
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Independent	0%	28%	53%	18%	1%	0%	0%	0%	0%	0%
synced	0%	9%	27%	32%	20%	10%	2%	0%	0%	0%

For the 10-year horizon under independent boundary conditions, the forecast produced no scenario with greater than 5 companies defaulting in the same year, as compared to 12% of such risk under synchronized boundary conditions. Similarly, the independent boundary conditions forecasted only 1% of scenarios with 4 companies defaulting at the same time, as compared to 20% of such risk under synchronized boundary conditions.

Conclusion

The current paper introduces one approach that incorporates a company's multiple dimensional financial state, as embodied by the balance sheet, into a dynamical model. The approach enables fundamental credit analysis to algorithmically forecast default and valuate debt based only on a company's financial statements and macro boundary conditions. The approach is particularly useful in evaluating the risk of multiple companies with its ability to forecast joint default based on operational correlation and shared macro boundary conditions.

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Model settings for Chinese real estate industry

Balance sheet fields

Model balance sheet fields	Corresponding fields in the financial statement
Cash	Cash and equivalent, restricted cash, liquid financial investments
Inventory	Inventory under processing, completed inventory, deposit paid for land acquisition
Capacity	Fixed asset, property plants & equipment
Receivable	Account receivables
Investment	Holding in JV and associates, investment properties
Related loans	Amount due from related parties
Tax receivable	Tax receivable, deferred tax asset
Payable	Account payable, amount due to related parties
Debt	Bank loans, senior bonds, corporate bonds, convertible bonds
Deferred Revenue	Contracted sales
Tax payable	Tax payable, deferred tax liability
Equity	Total shareholder’s equity

Elementary actions and parameters

Actions	Parameters
Sell equity	Amount
Add debt	Amount, coupon, maturity
Pay debt interest	Capitalization percentage
Pay maturing debt	
Presell inventory in processing	Inventory age, margin, delivery time, percentage of inventory, ratio of proceeds to total value
Buy inventory	Amount, LTV, payable percentage, loan interest, loan maturity

Processing inventory	LTV, payable percentage, loan interest, loan maturity
Delivery of presold inventory	Inventory age, percentage of presale delivered
Mark up un-presold and completed inventory	Margin
Sell newly completed inventory	Percentage sold, receivable percentage
Sell completed and aged inventory	Percentage sold, receivable percentage
Pay inventory sales and marketing cost	Cost margin to inventory
Depreciate capacity	
Receive investment returns	Percentage
Revalue investment	Percentage
MTM investment	
Sell investment	Amount
Receive receivable by age	Age of receivable, percentage received
Redeem loans to related parties	Loan age, percentage collected
Receive interest on loans	Interest rate
Pay tax	Tax rate, tax receivable percentage, tax payable percentage
Pay down payable by age	Payable age, paydown percentage
Lend loans to related parties	Amount
Distribute dividends	Amount
Buy back equity	Amount
Make investment	Amount
Buy fixed asset (PPE)	Amount, payable percentage, LTV, loan rate, loan term

Simulated parameters

Random	Presale percentage of 1 year old inventory
	Presale margin of 1 year old inventory
	Sales percentage of newly completed inventory
	Sales percentage of aged and completed inventory
	Delivery percentage of presales made a year ago
	Amount of loans lent to related parties
Planned	Amounts of new debt borrowed
	Amount of new inventory purchased
	Payables paydown percentages
Bounded	Growth rate of total debt
	Growth rate of total debt plus payable
Manually set	Equity raising is set to 0
	MTM gain of investment is set to 0
	Sales of aged inventory is set to be normal distribution (0, 10%)
Static	Remaining action values are set as constants equal to their average values of 2018, 2019 and 2020.

Optimization goals for planned parameters

All plannings are assumed to be made over 5-year horizon. The goals are to avoid default, or maximally delay the time of default, or maximize cash level at the time of default.

Distribution of leverage-based maximal annual debt growth rate

Max debt growth rate		**Percentile**						
		25%	**50%**	**75%**	**90%**	**95%**	**99%**	**100%**
	[0, 0.5)	25%	50%	75%	100%	150%	250%	250%

Debt-to-equity ratio	**[0.5, 1)**	15%	35%	50%	75%	100%	175%	175%
	[1, 2)	10%	25%	35%	50%	75%	150%	150%
	[2, 4)	0%	15%	25%	35%	45%	50%	50%
	>=4 or <0	-10%	0%	5%	15%	25%	38%	38%

For example, in the case of total debt, if the current debt-to-equity ratio is above 0.5 and below 1, there is a 25% probability that the debt growth is capped at 15%, a 50% probability that debt growth is capped at 35%, a 75% probability that debt growth is capped at 50%, a 90% probability that growth is capped at 75%, etc.

Asset liquidation prices

Assumed asset liquidation prices: inventory 50% (after matching off deferred revenue at 100% book value), investment 80%, loan to related parties 80%, fixed asset 50%, receivable 50%, tax receivable 100%.

Liability seniority order

The liability seniority order: tax payable, deferred revenue, senior secured debt, payable, senior unsecured debt, and equity.

Secured vs unsecured debt

The percentage of senior secured debt in all senior debts is fixed based on the disclosure in each company's financial statement, and the values are provided in Table 9.

Simulation paths

100 Monte Carlo paths are run for each company over 12 to 14 annual time steps. The actual number of scenarios computed is substantially higher due to the sub-simulations performed for the planned variables at each time step. The total number of scenarios computed for one company is roughly 100 x (21 + 11 + 11) = 4300 for each company.

Tables of results

Table 6. Annual default probability

Company	**Year**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Longfor	0%	2%	3.1%	2.1%	0%	1.1%	0%	0%	2.2%	0%
Vanke	0%	8.0%	20.7%	15.15%	9.7%	16.1%	21.3%	13.5%	12.5%	17.9%
Co Garden	0%	24%	17.1%	9.5%	10.5%	2%	4%	2.1%	2.1%	0%
Shimao	0%	5%	5.3%	8.9%	8.5%	5.3%	5.6%	10.4%	1.7%	3.4%
Agile	0%	0.0%	3.0%	6.2%	4.4%	4.6%	1.2%	2.4%	0%	3.8%
Greentown	0%	12.0%	13.6%	17.1%	23.8%	22.9%	32.4%	20%	35%	7.7%
Yuzhou	0%	11.0%	23.6%	29.4%	45.8%	38.5%	31.2%	36.4%	42.9%	50.0%
Sunac	0%	4.0%	9.4%	11.5%	15.6%	13.8%	16.1%	4.3%	4.4%	11.6%
Evergrande	0%	40.0%	38.3%	51.4%	27.8%	46.2%	57.1%	33.3%	50.0%	0.0%

Table 7. Precision limit of the forecasted annual default probability

Company	**Year**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Longfor	1.0%	1.0%	1.0%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%
Vanke	1.0%	1.0%	1.1%	1.4%	1.6%	1.8%	2.1%	2.7%	3.1%	3.6%
Co Garden	1.0%	1.0%	1.3%	1.6%	1.8%	2.0%	2.0%	2.1%	2.1%	2.2%
Shimao	1.0%	1.0%	1.1%	1.1%	1.2%	1.3%	1.4%	1.5%	1.7%	1.7%

Agile	1.0%	1.0%	1.0%	1.0%	1.1%	1.1%	1.2%	1.2%	1.2%	1.2%
Greentown	1.0%	1.0%	1.1%	1.3%	1.6%	2.1%	2.7%	4.0%	5.0%	7.7%
Yuzhou	1.0%	1.0%	1.1%	1.5%	2.1%	3.8%	6.2%	9.1%	14.3%	25.0%
Sunac	1.0%	1.0%	1.0%	1.1%	1.3%	1.5%	1.8%	2.1%	2.2%	2.3%
Evergrande	1.0%	1.0%	1.7%	2.7%	5.6%	7.7%	14.3%	33.4%	50.0%	100.0%

Table 8. Cumulative default probability

Company	Year									
	1	2	3	4	5	6	7	8	9	10
Longfor	0.0%	2.0%	5.0%	7.0%	7.0%	8.1%	8.1%	8.1%	10.1%	10.1%
Vanke	0.0%	8.0%	27.0%	38.1%	44.1%	53.1%	63.1%	68.1%	72.1%	77.1%
Co Garden	0.0%	24.0%	37.0%	43.0%	49.0%	50.0%	52.0%	53.0%	54.0%	54.0%
Shimao	0.0%	5.0%	10.0%	18.0%	25.0%	29.0%	33.0%	39.9%	41.0%	43.0%
Agile	0.0%	0.0%	3.0%	9.0%	13.0%	17.0%	18.0%	20.0%	20.0%	23.0%
Greentown	0.0%	12.0%	24.0%	37.0%	52.0%	63.0%	75.0%	80.0%	87.0%	88.0%
Yuzhou	0.0%	11.0%	32.0%	52.0%	74.0%	84.0%	89.0%	93.0%	96.0%	98.0%
Sunac	0.0%	4.0%	13.0%	23.0%	35.0%	44.0%	53.0%	55.0%	57.0%	62.0%
Evergrande	0.0%	40.0%	63.0%	82.0%	87.0%	93.0%	97.0%	98.0%	99.0%	99.0%

Table 9. Average recovery rate of senior unsecured debt upon default

Company	% Debt secured#	Year								
		1	2	3	4	5	6	7	8	9	10
Longfor	30%		77.4%	84.4%	92.4%		99.1%			73%	
Vanke	10%		45.2%	42.7%	40.6%	37.6%	38.9%	28.3%	37.6%	37.7%	35%
Co Garden	35%		0%	8.6%	22.9%	16.9%	43.5%	0.7%	0%	19%	0%
Shimao	40%		39.6%	51.9%	8.6%	46.9%	44.3%	58.6%	56.3%	8.7%	60.8%
Agile	50%			37.4%	26.9%	40.8%	28.6%	43%	24.1%	0%	26.9%
Greentown	40%		40.4%	42.3%	33.1%	34.2%	35%	33.1%	23.7%	23.7%	32.5%
Yuzhou	30%		42.4%	38.8%	39.1%	32.8%	34.8%	28.1%	30.1%	27.2%	19.9%
Sunac	80%		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Evergrande	30%		13.4%	14.5%	18.2%	16.6%	5.5%	3.1%	0.0%	37.4%	

Senior secured debt as % of all senior debt

Table 10. Fair-value par coupon rates of senior unsecured debt (%)

Company	Maturity year									
	1	2	3	4	5	6	7	8	9	10
Longfor	0.08	0.39	0.66	0.88	1.07	1.25	1.43	1.51	1.66	1.77
Vanke	0.08	2.45	6.11	7.25	7.47	8.19	9.27	9.44	9.54	9.85
Co Garden	0.08	13.8	15.3	14.2	13.9	12.6	12.0	11.3	10.8	10.2
Shimao	0.08	1.71	2.25	2.98	3.64	3.89	4.03	4.33	4.3	4.31
Agile	0.08	0.16	0.97	2.21	2.65	3.10	3.13	3.22	3.14	3.36
Greentown	0.08	3.97	5.67	7.53	9.45	10.5	11.9	12.3	13.1	13.0
Yuzhou	0.08	2.99	6.80	10.3	13.6	15.0	16.0	16.5	16.9	16.9
Sunac	0.08	2.20	4.94	6.97	9.01	10.0	11.1	10.7	10.5	10.8
Evergrande	0.08	21.8	27.8	32.9	33.0	34.4	35.6	35.7	35.8	35.7

Table 11. Expected forward shareholder's equity (in multiples to the current equity level)

Company	Years									
	1	2	3	4	5	6	7	8	9	10
Longfor	1.1	1.3	1.4	1.6	1.8	2.1	2.4	2.7	3	3.5
Vanke	1.1	1	0.9	0.8	0.7	0.7	0.6	0.6	0.6	0.5
Co Garden	1.1	1	0.9	1	1	1.1	1.3	1.4	1.6	1.9
Shimao	1	1.2	1.2	1.3	1.3	1.4	1.5	1.5	1.7	1.8
Agile	1.1	1.2	1.3	1.3	1.4	1.5	1.7	1.9	2.2	2.4
Greentown	1.0	0.8	0.7	0.6	0.4	0.3	0.2	0.2	0.1	0.1
Yuzhou	0.9	0.9	0.7	0.5	0.3	0.2	0.1	0.1	0.1	0
Sunac	1.1	1.1	1.1	1.1	1.0	1.0	1.0	1.0	1.1	1.1
Evergrande	1.0	0.6	0.3	0.2	0.1	0.1	0	0	0	0

Table 12. Distribution of scenarios in maximal number of companies defaulted in the same year

	Maximal number of companies defaulted in the same year									
	0	1	2	3	4	5	6	7	8	9
Over 5 years	6%	19%	27%	21%	17%	8%	2%	0%	0%	0%
Over 10 years	0%	9%	27%	32%	20%	10%	2%	0%	0%	0%