

Corporate Cash Flow Shortfall Risk Analysis Based on Monte Carlo Simulation: Evidence from a Chinese Manufacturing Enterprise

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Abstract: For Chinese companies, especially manufacturers, cash flow has become a critical issue in their survival, given that they rely heavily on short-term bank borrowing and extend generous trade credit to downstream customers. The traditional diagnostics that are based on ratios provide information about past liquidity, but not about the likelihood that future liquidity will be insufficient for a firm's operations. In this paper, a Monte Carlo simulation model for estimating corporate cash flow shortfall risk is developed. The variables that are subject to random variation are formulated as random variables: revenue growth, the ratio of receivables collected, the ratio of variable costs, the ratio of payments to suppliers, and fixed cash expenses. The path of the cash balance generated by these variables is then simulated for a one-year period, quarterly. The framework is applied to an anonymized medium-sized Chinese machinery manufacturer whose input distributions have been calibrated to published financial statements, and industry norms. Across 10,000 iterations, the chance of falling below the minimum operating cash floor within one year is 11.83 percent, most of it in the fourth quarter when a large loan repayment is due. At a 95 percent confidence level, cash flow at risk reaches 107.0 million RMB relative to the expected outcome. Sensitivity analysis identifies the collection ratio as the largest risk factor, while scenario tests show that deferring part of the year-end debt maturity, together with a two-point increase in the collection ratio, reduces the shortfall probability to less than 1 percent. Robustness tests on sampling error, alternative random seeds, heavier-tailed shocks and correlated inputs confirm the reliability of the estimates, and suggest that the assumed independence between demand and collections is the assumption to which the results are most sensitive. The study shows that the application of a set of shortfall metrics based on simulation is a viable complement to existing financial risk early warning indicators for Chinese enterprises with a clear forward-looking perspective.

Keywords: Monte Carlo simulation, cash flow at risk, liquidity risk, financial risk management, Chinese enterprises, shortfall probability.

1. Introduction

Profitability and solvency are viewed as the two key pillars of corporate health, but many companies that show a profit turn out to be unsuccessful because cash is received after liabilities are due. This tension is particularly apparent in China, where manufacturing enterprises frequently borrow short-term from banks to fund their working capital and then have to pay them back or renew the loans within a year, but it takes several months for their receivables from downstream customers to be cashed. A company can find itself in a liquidity crisis even though its order book is strong, if credit conditions tighten up or a big payment falls in a weak collection quarter. The key issue for managers and lenders is not whether cash flow is adequate this year, but how likely it is to be inadequate next year, by how much, and when.

The problem is sharpened by the macroeconomic context. The receivables collection time has been steadily increasing for Chinese industrial companies over the last ten years, as big customers extend payment terms and a larger proportion of the invoices are paid on delayed terms with commercial acceptance bills. Meanwhile, deleveraging policy and the contraction of informal credit channels have made the rollover of short-term bank facilities less automatic, especially for private and mid-sized enterprises that have not been guaranteed implicitly. The mix is dangerous: cash coming in flows later in the operating cycle but the biggest cash outflows – loan repayments – are fixed in the calendar. The corporate stress scenarios of the recent years have had

this pattern over and over again: When a company is on the brink of being in distress, it is facing a weak collection period and a cluster of maturities at the same time, but it cannot cover them all in time. There is a need for a method of measuring this exposure which treats the drivers of cash flow as uncertain quantities and tracks their joint impact over time.

Specifically, the study seeks to answer three questions: First, how likely is it that a typical Chinese manufacturing company, with a typical source of financing, will violate its minimum operating cash requirement within a year? And when in that year is the most likely time for the company's cash flow to fall below the minimum requirement? Second: What are the most significant cash flow drivers of the "randomness" and what is the funding shortfall if and when it happens? Third, what are the most effective management interventions and do standard prescriptions perform worse than intuition suggests when the complete cash trajectory is considered?

Conventional financial analysis is not designed to give satisfactory answers to these questions. Liquidity ratios, coverage ratios, and trend extrapolation compress an uncertain future into a single deterministic number and offer no probability statement about what could go wrong. Monte Carlo simulation directly overcomes this limitation. The method assigns probability distributions to the cash flow drivers and repeatedly draws samples from these distributions, resulting in a probability distribution of future cash flow outcomes from which the tail risks can be read off directly. It has been successfully employed in financial engineering, for

example in the pricing of derivatives, in sensitivity analysis and in computing value-at-risk [1] and also in the context of investment risk assessment, where its systematic description has been provided in the context of simulation literature [2]. Because of its ease of access in spreadsheet form, it has also been a useful tool for making a variety of business decisions, including selecting a portfolio and deciding on inventory or project [3].

Because of the relevance of the problem to Chinese enterprises, this paper takes the simulation approach to address the problem of running out of operating cash resources and quantifies the risk. Three contributions are made. First, a compact quarterly cash balance model is developed where the revenue growth, the collection of receivables, the ratios of the costs, the payment behavior of suppliers, as well as scheduled debt service, all influence cash flow along the path, and the risk of cash shortfall is measured on the path minimum rather than on a single terminal value. Second, the model is applied to an anonymized mid-sized Chinese machinery manufacturer, producing concrete estimates of the shortfall probability, its timing, cash flow at risk, and the conditional expected deficit. Third, sensitivity and scenario analyses translate the statistical output into managerial levers, showing which interventions reduce risk efficiently and, just as importantly, which seemingly reasonable interventions can backfire.

2. Related Work

2.1. Financial Risk Early Warning for Chinese Enterprises

A substantial body of research has grown around early warning models for the financial risk of Chinese firms, most of it built on machine learning classifiers trained on financial statement indicators. Li applied deep neural networks to warn of financial risk in manufacturing listed companies, screening indicators with nonparametric tests before training the network and obtaining satisfactory forecasting performance for state-owned listed firms [4]. Liu and Yang combined rough set theory for feature selection with a back-propagation neural network, reporting accuracy above 95 percent in classifying the risk status of listed companies [5]. Related work has extended intelligent techniques to adjacent tasks: Yao examined the application of artificial intelligence in enterprise financial auditing [6], and Zhao and Wang proposed a big-data-driven auditing method based on convolutional neural networks [7]. These studies confirm that data-driven models can recognize distress patterns effectively. Their common output, however, is a classification or score, which indicates that a firm resembles previously distressed firms but does not state the probability, magnitude, or timing of a future cash shortfall.

Two further limitations of the classification paradigm are worth noting because they motivate the present approach. The first is a labeling issue: distress labels for listed Chinese companies are typically assigned to companies that receive special treatment or undergo delisting, which occurs infrequently, with a lag time and is influenced by the regulatory process, making the training signal sparse and noisy. The second is a mechanism issue: a correct classification indicates that a firm is similar to the failures of the past but does not identify why the firm may fail, and managers don't know what lever to pull. A structural simulation, on the other hand, explicitly models causal

accounting relationships, and outputs directly relate to choices of collections, payment terms, and maturity scheduling.

2.2. Data-Driven Modeling of Financial Uncertainty

A second stream models financial time series directly by deep learning. Mehtab et al. presented a CNN-LSTM based stock price analysis system with good performance [8], Chong et al. enhanced stock market prediction using ensemble deep networks [9] and Guo et al. introduced a hybrid multi-scale residual CNN-LSTM model for cryptocurrency price prediction [10]. These techniques are especially well suited to identifying patterns from a dense set of market data, but corporate cash flow is a different scenario: observations are sparse (quarterly at most), the structure of revenue, collections, cost and debt service is well known, and the object of interest is a tail probability, not a point forecast. Structural stochastic simulation is more suitable to these circumstances, as it explicitly incorporates the accounting identities and only uses the data to determine the input distributions.

2.3. Simulation-Based Downside Risk Measurement

The third of these, which is most closely related to this paper, applies Monte Carlo techniques to the calculation of downside risk measures. Astiti et al. used the Monte Carlo simulation method to calculate value at risk for cryptocurrency portfolios, and showed how to use return distributions from the simulated portfolios for explicit statements of tail risk [11]. The computational side of this stream is also progressing quickly: Egger et al. worked on implementing Monte Carlo-style credit risk analysis on quantum hardware, where they suggested significant acceleration for workloads involving risk estimation [12]. The incorporation of these portfolio-oriented measures into the operating cash flow of a nonfinancial enterprise is relatively undeveloped; the risk at the operating level is not of a change in market price, but of the combination of collections, costs, and lumpy debt maturities. The cash-flow-at-risk view used in this context addresses this question in the Chinese business environment.

2.4. Research Gap and Positioning

Combining the three strands, a clear division of labor emerges. Early warning classifiers identify that something is wrong; deep forecasting models forecast what a market series is likely to do next; simulation-based risk measures state how bad an outcome can be and the probability of the occurrence. For the liquidity problem facing Chinese enterprises, the third capability is the one that matters, yet published applications of simulation-based downside measures concentrate on traded portfolios, where risk factors are prices, rather than on operating firms, where risk factors are collections, costs, and maturities. This paper occupies that intersection. It borrows the tail-oriented measurement logic of the value-at-risk literature, replaces market risk factors with the working capital and financing variables that govern a manufacturer's cash position, and defines the risk event on the trajectory of the cash balance, a formulation that, as the results will show, has substantive consequences for how debt restructuring should be evaluated.

3. Methodology

3.1. Cash Balance Model

Consider a planning horizon of T quarters indexed by $t = 1, \dots, T$. Accrual revenue evolves multiplicatively,

$$R_t = R_{t-1} (1 + g_t) \quad (1)$$

Where g_t is the stochastic quarterly growth rate and R_0 is the most recent observed quarterly revenue. Cash actually collected in quarter t is $c_t R_t$, where c_t denotes the collection ratio, the share of current revenue converted to cash within the quarter. On the outflow side, variable production costs equal $v_t R_t$, of which a share p_t is settled in cash during the quarter (the remainder being financed by supplier credit); fixed cash expenses are F_t ; cash taxes and fees are approximated as a proportion τ of the nonnegative operating margin; and D_t denotes contractually scheduled debt service, comprising interest and principal repayments. The net cash flow of quarter t is therefore

$$CF_t = c_t R_t - (p_t v_t R_t + F_t + \tau \cdot \max(R_t - v_t R_t - F_t, 0) + D_t) \quad (2)$$

And the end-of-quarter cash balance follows the recursion

$$B_t = B_{t-1} + CF_t, \quad B_0 = \text{initial cash.} \quad (3)$$

A shortfall occurs when the balance falls below the minimum operating cash floor $B_{\min}$, the level below which the firm cannot reliably meet payroll, utilities, and routine settlement obligations. Because insolvency is triggered by the first breach rather than the year-end position, risk is defined on the path minimum. Three measures summarize the simulated distribution: the shortfall probability

$$P_s = P(\min_t B_t < B_{\min}) \quad (4)$$

The cash flow at risk at confidence level α , defined as the difference between the expected annual net cash flow and its $(1 - \alpha)$ quantile,

$$CFaR\alpha = E[CF_{\text{ann}}] - Q_{1-\alpha}(CF_{\text{ann}}) \quad (5)$$

And the conditional expected deficit, the mean of $B_{\min} - \min_t B_t$ computed over shortfall scenarios only, which indicates how much external funding would typically be needed once a shortfall materializes.

The following three modeling decisions are explained briefly. The quarterly time step is the same as the one used when Chinese companies report, and is the time frame on which treasury decisions are made about facilities and buffers; a smaller time step would have little impact since the most important lumpy outflows are known maturity dates. This definition of the risk event on the way to the minimum (as opposed to the terminal), instead of the balance, reflects the institutional reality that if a firm fails to pay in the second quarter, it is in default; this is analytically important when comparing maturity structures. Finally, cash taxes are approximated as being proportional to the nonnegative operating margin because taxes are a second-order cash item, relative to procurement and debt service, at this horizon, with the max operator ensuring that the model does not produce unrealistic tax refunds in loss quarters.

3.2. Stochastic Inputs

Five inputs are treated as random variables. The demand uncertainty is represented as growth g_t , which is drawn from a normal distribution. The collection ratio c_t , the variable cost ratio v_t and supplier payment ratio p_t are sampled from

truncated normal distributions bounded within economically plausible ranges, capturing, respectively, receivables quality, input cost pressure and the firm's own use of trade credit. There is a relatively small multiplicative noise term in the fixed expenses. The baseline assumes that the draws are independent across quarters and between variables, which is relaxed in the robustness analysis in Section V and reexamined in Section VI. The specifications used in case study are given in Table I.

The ratio variables were preferred to be truncated normal instead of being unbounded for two reasons. From an economic point of view, ratios like collections and payments are constrained to a reasonable range by contract and by accounting identity and an unbounded distribution would give probabilities to states that are impossible. The two-parameter normal form is, statistically speaking, a judicious choice since only a few years of quarterly observations are available for calibration; with such a short sample, fitting flexible distributions risks encoding noise, whereas a form calibrated to the observed mean and dispersion and then bounded by judgment is transparent and easy for practitioners to audit and update.

3.3. Simulation Procedure

The process goes as follows. The first one is the sampling of the joint input vector for all quarters. Second, the equations (1)-(3) are calculated to obtain one full cash balance path. Thirdly, the path minimum, the net cash flow over the year and the breach indicator are all logged. This procedure is repeated $N = 10,000$ times and finally the risk measures (4) and (5) are estimated from the empirical distribution. The running estimate of the shortfall probability was used to verify the convergence; after 2,000 iterations, the estimate was 12.00 percent; after 5,000 iterations, the estimate was 11.84 percent; and after 10,000 iterations, the estimate was 11.83 percent. Sensitivity is measured using Spearman rank correlations between each input, averaged over the year, and the annual net cash flow, which is a good option because of the nonlinearities arising from the truncation and max operator in (2). The simulation was implemented in Python with a fixed seed for reproducibility.

The sampling error for the shortfall probability is estimated as the mean of a binary indicator, and so the sampling error will be given by the binomial formula, with the standard error being the square root of $p(1 - p)/N$. This gives a standard error of about one-third of a percentage point for probabilities in this range and $N = 10,000$, which is small enough that the substantive findings are not sensitive to simulation noise. The resulting confidence interval is reported in Section V alongside checks with alternative seeds, a larger sample, heavier-tailed growth shocks, and correlated inputs.

4. Case Study: A Chinese Manufacturing Enterprise

The framework is applied to Company H, an anonymized medium-sized machinery company in the Yangtze River Delta. The firm is typical of a major class of industrial companies in China: annual revenue of roughly 1.9 billion RMB, thin operating margins, receivables of about 25 percent of revenue outstanding at any given time, and working capital financed primarily via 1-year bank facilities which are due to be paid back around the end of the fiscal year. Input distributions were adjusted to fit the patterns that could be

seen in the company's published financial statements and to norms for Chinese listed machinery companies; identifying information has been modified and names or figures should be considered as a reflection of a realistic calibration and not as an audited set of figures. The values of the parameters are shown in Table I.

Table I. Model Parameters for Company H (values in million RMB where applicable)

Input	Specification	Interpretation
Base quarterly revenue R_0	480	Most recent quarterly revenue
Revenue growth g_t	$N(1.5\%, 3.0\%)$	Demand uncertainty
Collection ratio c_t	$N(0.90, 0.05)$, on $[0.75, 0.99]$	Receivables conversion within the quarter
Variable cost ratio v_t	$N(0.71, 0.03)$, on $[0.60, 0.85]$	Materials, energy, direct labor
Supplier payment ratio p_t	$N(0.88, 0.04)$, on $[0.75, 1.00]$	Share of variable cost settled in cash
Fixed cash expenses F_t	$70 \times N(1.00, 0.05)$	Overheads, salaries, rent
Cash tax rate τ	10%	Applied to nonnegative operating margin
Debt service D_1-D_4	30 / 60 / 30 / 120	Scheduled interest and repayments
Opening cash B_0	140	Balance at the start of the horizon
Cash floor $B_{\min}$	60	Minimum operating cash requirement
Iterations N	10,000	Fixed random seed

The cash flow analysis is a challenging test in the machinery sector. Within the construction, energy and heavy industry sectors, orders are frequently project-based with milestone billing, meaning that the timing of revenue recognition and cash receipt can be months apart; customers in these industry sectors often pay acceptance bills, which only turn into cash at maturity or at a discount; and

competition means that advance payment is often not acceptable. The calibration was done in three steps. The growth rate, cost ratios and collection behavior were derived from three-year averages of quarterly statements from the firm, the collection ratio being inferred from the relationship between reported revenue and the change in receivables. The quarter-to-quarter range of variability for the same series was used as the dispersion parameters, and these were compared with similar firms listed in the machinery category as to ensure that a short sample did not underestimate the volatility; and the debt service schedule was retrieved directly from the firm's loan contracts.

Two aspects of the calibration need to be highlighted in view of common practices among Chinese manufacturers. The collection ratio averages 0.90 with meaningful dispersion, reflecting the lengthy payment terms that dominate business-to-business trade in the sector. And debt service is very back-loaded, with the 120 million RMB obligation coming due in the fourth quarter and equalling the maturity of a one-year working capital loan, a typical facility that firms routinely anticipate being able to roll over but which is a real cash commitment when refinancing is postponed or reduced.

5. Results and Discussion

5.1. Distribution of Annual Net Cash Flow

The simulated distribution of annual net operating cash flow is shown in Fig. 1. The average is minus 3.2 million RMB and the standard deviation is 64.6 million, so the firm will probably have little cash flow surplus or deficit with significant variation from that level. At the 5th percentile, the cash flow is -110.1 million, while at the 1st percentile, it is -151.4 million, with the cash flow “at risk” at the 95 percent level of 107.0 million relative to the mean. A projection based on expected values alone would show that the year is more or less cash neutral and therefore uninteresting; the simulated distribution shows that a one-in-twenty outcome uses up most of the firm's opening liquidity.

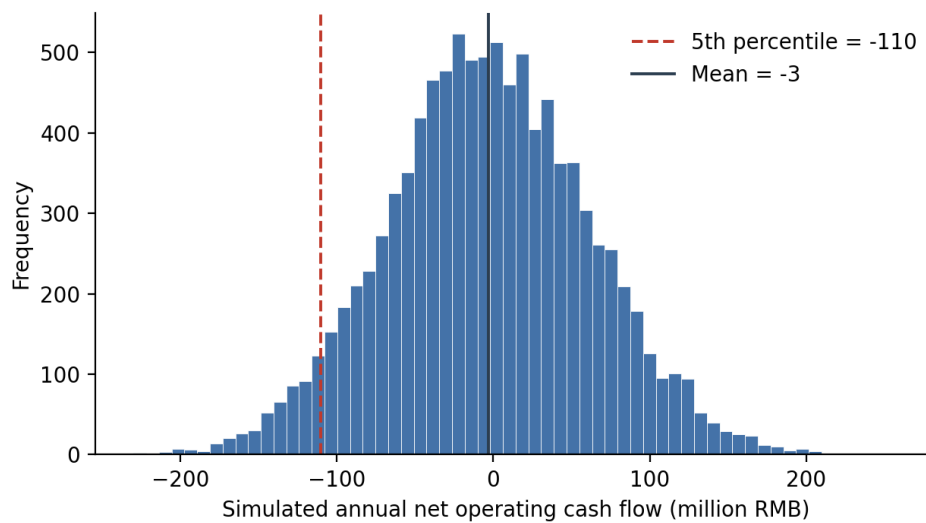


Figure 1. Simulated distribution of annual net operating cash flow (10,000 iterations)

5.2. Shortfall Probability and Its Timing

There is an 11.83% chance that the cash balance will cross the operating floor of 60 million RMB at least once during the year. This risk is broken down by quarter and it is seen that it is almost entirely in the fourth quarter, with the marginal breach probability being negligible in the first, less than 1%

in the second and third quarters and 11.68% in the fourth quarter (when the 120 million loan maturity falls due). If the shortfall actually happened, then, based on the expected shortfall below the floor, the size of the bridge financing the firm would normally be required to arrange is 31.4 million RMB. The timing result is very clear – the risk is not evenly

distributed over the year but rather focused around maturity dates, and the greatest frictions to refinancing are likely to

happen at those dates.

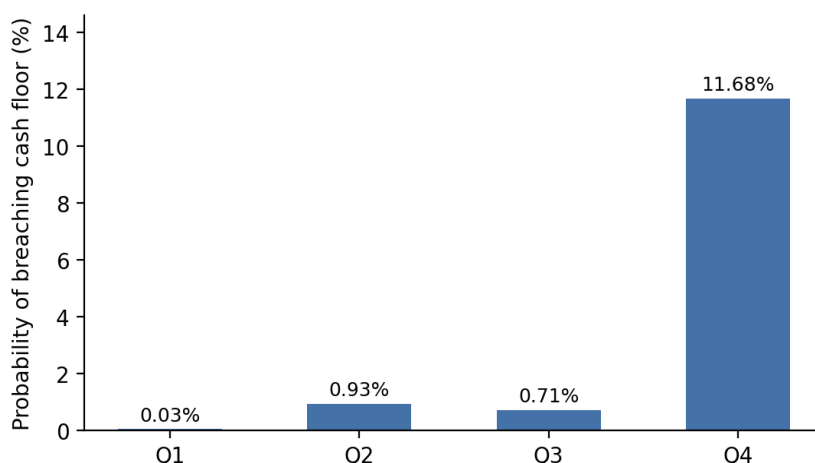


Figure 2. Marginal probability of breaching the cash floor by quarter

5.3. Sensitivity Analysis

In Fig. 3 the input variables are ranked in order of the Spearman rank correlation between their annual averages and annual net cash flow. The collection ratio is the most correlated with +0.74 followed by the supplier payment ratio at -0.42, the variable cost ratio at -0.35, the revenue growth at +0.27 and the fixed cost noise at -0.10. The order of the

items is informative. Often, managers focus on discussion of risk around the revenue side of the equation, but in this cash structure a percentage point of collections is worth a lot more than a percentage point of revenue growth; growth that is not collected simply increases the size of the receivables, while the firm's obligations to pay on the cash side remain the same. Working capital behavior, on both the receivable and payable sides, is the main transmission channel of cash flow risk.

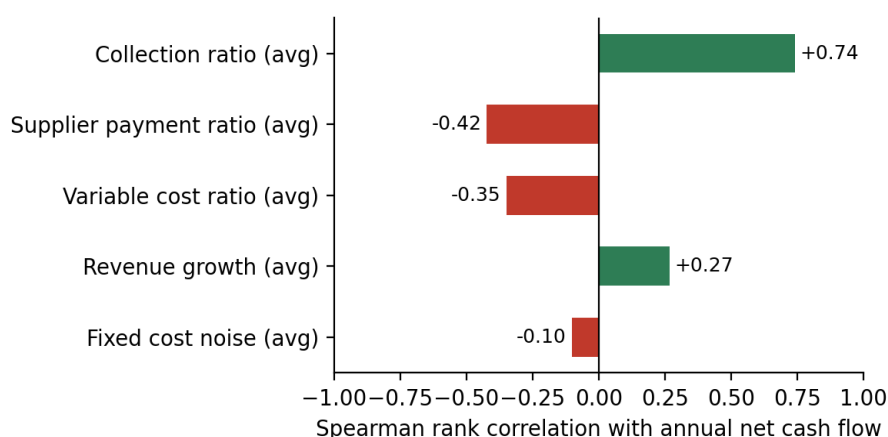


Figure 3. Sensitivity of annual net cash flow to model inputs (Spearman rank correlation)

5.4. Scenario Analysis and Managerial Implications

To assess five management interventions, the simulation was rerun under the same random seed with different sets of assumptions as shown in Table II. The probability of the shortfall is reduced from 11.83 percent to 4.01 percent by postponing 40 million RMB of the fourth-quarter maturity to be refinanced in the next year, which amounts to arranging partial refinancing in advance. The average collection ratio could be improved by 2 percentage points, either by tightening up credit policies or by getting invoices in earlier or by receivables factoring, which results in a similar reduction to 3.83 percent. The two measures when executed together lower the probability to below one percent. A higher buffer of cash is also beneficial, as the probability is lowered to 5.06 percent if the opening cash is increased from 140 million RMB to 170 million RMB, but comes at the cost of liquidity that may not be used.

One surprising result is of particular interest. By distributing debt service at a level of 60 million RMB a

quarter, which may seem sensible since it removes the big payment at the end of the year, the probability of a shortfall actually increases to 14.67 percent. The answer is the definition of risk, as the repayment path takes the buffer out in the early quarters before operating cash has time to build up, which means that the path gets to the bottom of the balance quicker and more often. A restructuring decision that is taken at a particular point because of the nature of the biggest obligation may be counterproductive as the risk of a shortfall is dependent on the whole 'life cycle' of the balance. This kind of information can not be obtained from a point estimate, but is possible with path-level simulation.

Table II. Shortfall Probability Under Alternative Scenarios

Scenario	Shortfall probability	Change vs. baseline
Baseline (Table I parameters)	11.83%	-
Defer 40 of the Q4 maturity beyond the horizon	4.01%	-7.82 pp
Collection ratio improved by 2 pp (0.90 → 0.92)	3.83%	-8.00 pp
Both measures combined	0.95%	-10.88 pp
Opening cash raised from 140 to 170	5.06%	-6.77 pp
Debt service smoothed to 60 per quarter	14.67%	+2.84 pp

The results, taken together, suggest an easy-to-understand program for risk management for companies in Company H's position: keep the simulated shortfall probability as a constant risk manager; pay attention to the performance of receivables, not necessarily to volume growth if liquidity is the constraint; design the maturity structure based on the simulated path of the balance, not the peak exposure; size cash buffers based on the conditional expected deficit, the amount of the funding shortfall that is likely to materialize in adverse scenarios. The design also integrates easily into the existing financial control process. The treasury function can also update the shortfall probability as statements close on a quarterly basis, in as few seconds as it takes, and report it as an internal key risk indicator, similar to how banks report their value at risk, and also link it to the board reporting. To start, the covenant design can be worked out backwards from the lender's point of view: If the lender is willing to accept that the risk of default will not exceed an agreed-on level, what is the minimum maturity schedule that will satisfy the borrower.

5.5. Robustness Checks

Four checks examine if the headline estimate is a simulation artifact or due to distributional assumptions. The first is sampling error: with $N = 10,000$, the binomial standard error of the estimated probability is 0.32 percentage point, with the 95 percent confidence interval for the estimate being 11.20 to 12.46 percent. The second is seed dependence: across five independent random replications of the full model the estimate ranged from 11.14 to 11.83 percent, a range of 0.69 percentage point that is in line with the theoretical sampling error, and 11.82 percent for an extended run of 50,000 iterations. Third, tail thickness: replacing the growth shocks by Student-t shocks with 5 degrees of freedom, scaled to the same standard deviation, only slightly shifted the estimate to 11.74 percent, since the binding risk is not caused by the tails of the growth shocks, but by the debt maturity schedule.

The fourth check is most important. Incorporating a positive correlation (0.5) between revenue growth and the collection ratio such that weaker growth also means weaker collection resulted in the shortfall probability rising to 13.61 percent, an increase of 1.8 percentage points, which is far larger than any other perturbation tested. The effect direction is intuitive: dependence between adverse drivers pushes probability mass toward conjunctions of bad states – where the cash floor is crossed. The practical lesson is that the baseline figure should be regarded as a mildly optimistic lower bound, and that firms in sectors where demand and payment discipline drop together during a downturn should adjust buffers to the correlated variant and not the independent one.

6. Conclusion

This paper has designed and tested a Monte Carlo model to calculate corporate cash flow shortfall risk, and applied it to a typical Chinese manufacturing company. Defining risk as the path minimum of the cash balance, as opposed to a terminal value, proved essential: it showed that the bulk of the risk was at the year-end loan maturity, produced interpretable measures of risk (shortfall probability, cash flow at risk and a conditional expected deficit), and showed that an apparently sensible smoothing of debt maturities can actually increase the risk if one considers the full trajectory of the cash balance. The sensitivity analysis results also showed that receivables collection was the most important factor, which is consistent with the working capital pressures widely reported among Chinese manufacturers.

The results are relevant to audiences beyond the firm itself. The study also implies that the borrower's repayment calendar is a risk parameter that is not typically represented in standard coverage ratios and should be explicitly priced and/or covenanted by banks that provide loans based on working capital. The sensitivity results justify policy interventions that will lead to faster conversion of cash, e.g. enforcement of prompt payments and access to receivables financing as these act on the variable to which the risk of cash shortages among manufacturers responds most. For intelligent financial risk management, generally, the design principle that is illustrated here is complementary: encode structure where it is known; leave statistical learning to the input distributions consumed by the structure.

The results are subject to some limitations which indicate future work. Independence of inputs was assumed in the baseline, and the robustness analysis indicated that plausible dependence between growth and collections increases the shortfall probability significantly, which is the most important extension that can be performed and would render the estimates more conservative. The one year quarterly time horizon is appropriate for working capital planning, but could be refined to a monthly resolution around known maturity dates. Input distributions were judgmentally estimated from financial statements; machine learning approaches similar to those described in Section II could also be applied to estimate such distributions and cross-validate the model with actual outcomes over a sample of firms. Lastly, as simulation workloads grow with richer dependence structures and smaller time steps, the new computational platforms such as the quantum approaches discussed above, could be relevant to enterprise scale deployments. This much the study demonstrates: Monte Carlo shortfall analysis transforms scattered accounting data into straightforward probability statements about the outcomes that matter most. And it can be done by modeling tools that are easily accessible to companies.

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