OLIVER WYMAN

ERCOT
THE TEXAS CONNECTION

Corporate Risk

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Finance & Audit Committee
Credit Evaluation Project Results

Austin, TX

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Contents

Section 1

Background

The entire credit evaluation project covered three workblocks

Workblock 1

Credit practices review

- Assessed ERCOT's current credit management practices
- Assessed ERCOT's current creditworthiness practices
- Examined nodal impacts

Workblock 2

Credit scoring model

- Developed a set of credit rating tools to assess probabilities of default (PD) for each participant
- Identified model factors based on financial data and qualitative assessments
- Tested against available benchmarks

Workblock 3

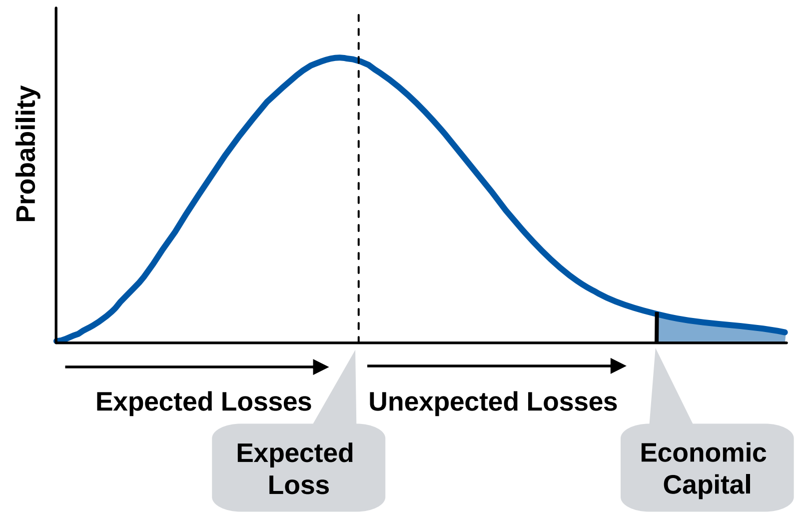
Credit loss model

- Included collateral limits, price caps, other key assumptions as inputs
- Looked at possible volumetric exposures for each participant
- Simulated market prices, which with the volumes yield exposure at default (EAD)
- Simulated losses from credit failures
- Explored the impact of exogenous variables/ stress events

Credit loss and capital adequacy definitions

- **Capital adequacy (economic capital):** Based on the **portfolio analysis** and an assessment of the market, it is the amount of losses you may lose over a specified time period with probability X%
- **Expected Loss:** Long run statistical average of potential credit losses across a range of typical economic conditions
- **Portfolio analysis:** Aggregation of losses by counterparty across the market

Illustrative Loss Distribution



Terms used when measuring credit loss

- **Probability of default**: The probability that a counterparty will default at some point in a specified time horizon
  - **Default correlation:** Similarity of the counterparty to other counterparties in the portfolio in terms of common drivers of default (e.g. geography, industry, business model)
- **Exposure at Default:** Sum of the exposures at time of default for each counterparty over the specified time horizon
- **Loss given default:** Sum of exposures **in excess of collateral and other risk mitigation** at time of default for each counterparty over the specified time horizon

Confidence levels in corporate finance

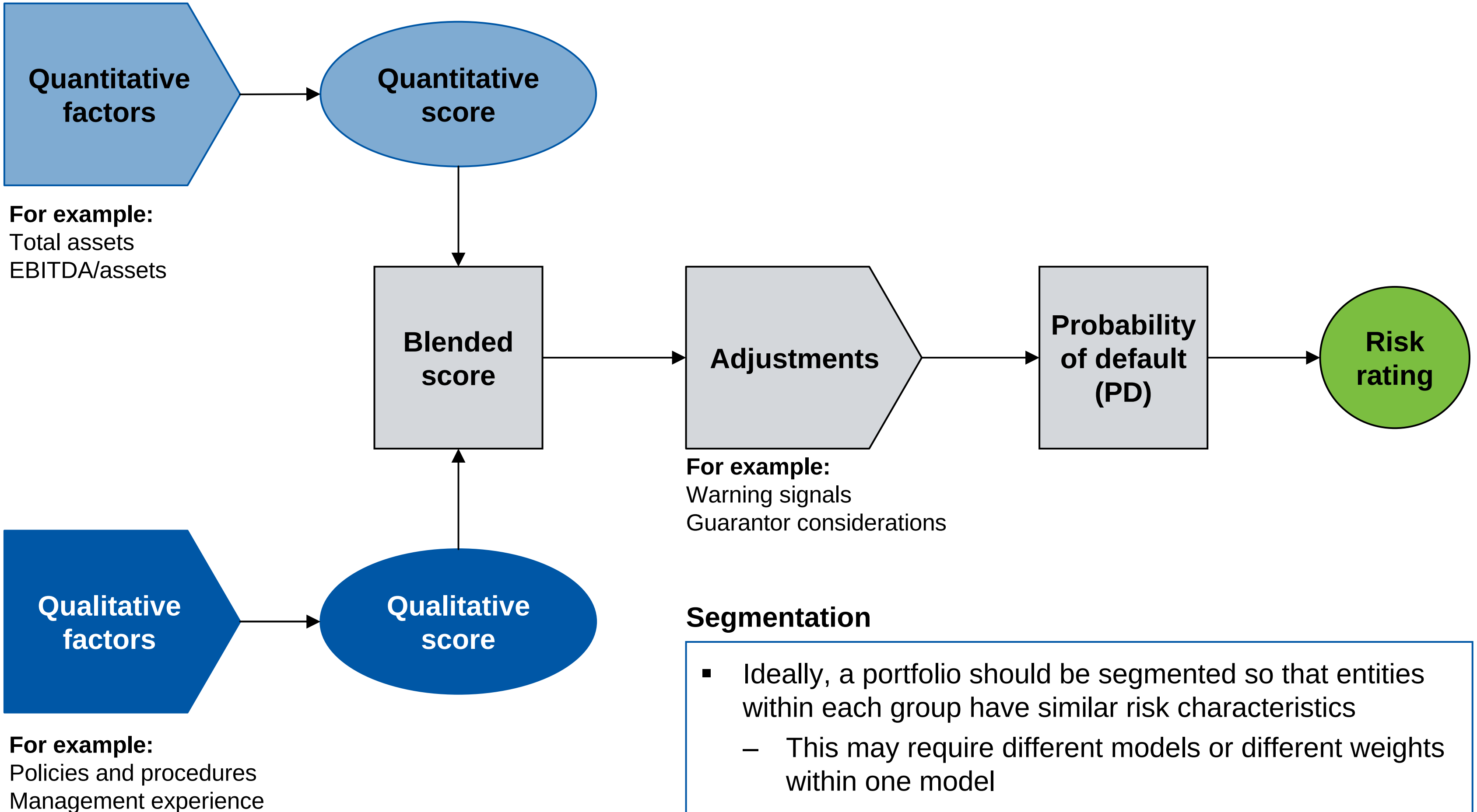
- This table shows historical default rates for firms with a variety of S&P credit ratings
- The "1-yr PD" is the likelihood a firm with this rating will default for any reason within one year.
- The "Confidence level" can be thought of as the likelihood that a firm with this rating will still be solvent after one year has passed, or the fraction of firms holding this rating that will remain solvent over the year
- Some firms use a target rating as a solvency standard
  - They manage their business so that the likelihood of bankruptcy within the next year equals the associated 1-yr PD
  - For example, if they target BBB+, the probability of insolvency must be about 0.1%
  - The amount of available assets the firm must hold to achieve this is its **economic capital requirement**

Rating	1-yr PD	Conf level
AAA	0.002%	99.9980%
AA+	0.003%	99.9970%
AA	0.005%	99.9950%
AA-	0.010%	99.9900%
A+	0.018%	99.9820%
A	0.033%	99.9670%
A-	0.059%	99.9410%
BBB+	0.108%	99.8920%
BBB	0.185%	99.8150%
BBB-	0.354%	99.6460%
BB+	0.642%	99.3580%
BB	1.164%	98.8360%
BB-	2.111%	97.8890%
B+	3.828%	96.1720%
B	6.943%	93.0570%
B-	12.59%	87.4080%
CCC+	22.84%	77.1620%

Section 2

Internal credit scoring

A standard credit scoring approach blends quantitative and qualitative scores and potential adjustments, to arrive at a PD and risk rating



Segmentation

- Ideally, a portfolio should be segmented so that entities within each group have similar risk characteristics
  - This may require different models or different weights within one model
- Segmentation of a portfolio can be performed along different dimensions (e.g., size, sector)

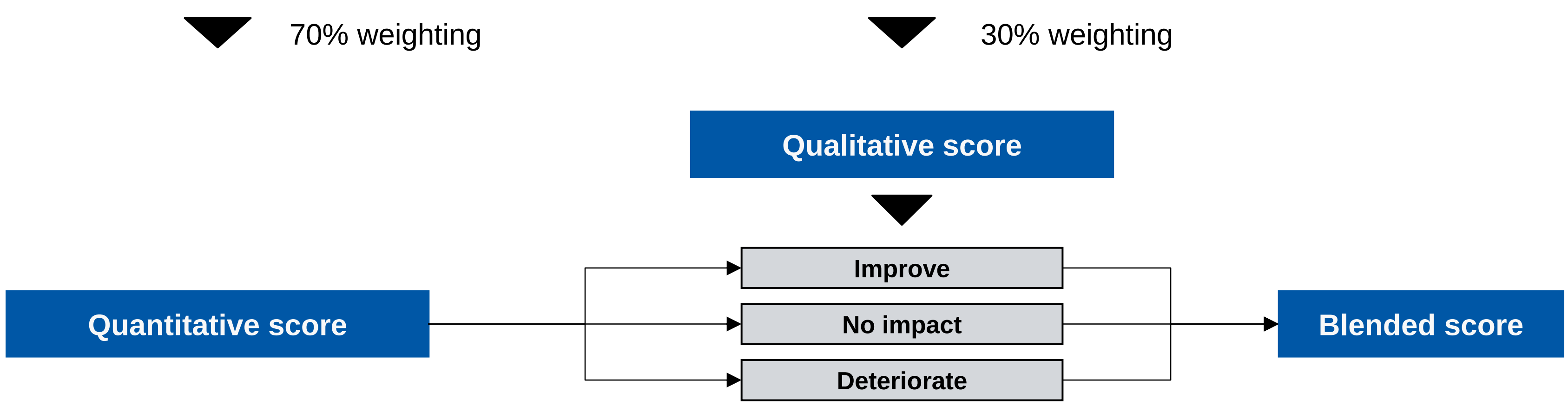
Selected financial and qualitative factors and weights

Quantitative factors

Proposed factor	Weight
Working Capital/Sales	30%
Current Ratio	10%
Equity/Assets	20%
EBITDA/Interest Expense	10%
EBITDA/Sales	10%
Net Income/Assets	10%
Total Assets	10%

Qualitative factors

Proposed factor	Weight
Ability to access funding in difficult market environment	25%
Margin call and late payment history	20%
Experience of company leadership	15%
Recent growth	15%
Risk management policies and practices	10%
Quality and timeliness of reporting of financial information	10%
Length of time as QSE	5%



The scoring approach groups output into a rating category with an associated midpoint PD so as not to overestimate precision

Example

Internal credit scoring model

Resulting PD

30bps

Map PD to a rating category

PD range (bps)	Rating	Midpoint PD (bps)
3-5	AAA-A+	4
5-10	A+-A-	8
10-15	BBB+	13
15-25	BBB	20
25-40	BBB-	33
40-80	BB+	60
80-135	BB	108
135-220	BB-	178
220-365	B+	293
365-600	B	483
600-1000	B-	800
> 1000[1]	CCC+	1500

Final output based on rating and midpoint PD

BBB 33bps

1. All lower PDs map to this rating

Credit scoring results are used as input for credit loss modeling

- Oliver Wyman used the model assumptions discussed on the previous pages to arrive at initial Probabilities of Default (PDs) for each QSE
  - Some of these were agency ratings
  - Some were scored based on financials provided to ERCOT
  - Others were assigned CCC+ when no financials were provided
- All of these initial ratings were considered in light of any relationship between the participant and a parent (i.e., “Group Logic” was applied)
- Credit loss model treats capped guarantees with 30-day termination clauses as collateral
  - Where the guarantee is substantially in excess of EAL, should net same results
  - Best allows for all possible scenarios where and how entities use guarantees

Section 3

Credit loss modeling

Credit loss modeling

The questions this type of model addresses center on the potential for credit-related losses

Expected Loss	Economic Capital		
What level of credit losses is "normal"?	**What is the greatest loss we can expect?**	**How can these numbers be reduced?**	**Do market rule changes impact the expected losses?**
▪ Quarterly or annually ▪ This loss amount will vary, and is considered the **expected loss** ▪ Business must accommodate these	▪ Over a given period ▪ For a given level of confidence ▪ Under a given set of assumptions ▪ Given a standard for solvency, can be used for determining **economic capital required**	▪ Impact of credit and collateral rules ▪ Through process changes; billing cycle, mass transition handling, market rules ▪ Monitoring effort enhancements	▪ Price cap levels ▪ Netting agreements ▪ New instruments or derivatives ▪ Bidding restrictions and rules

Approach

- **Model the inputs of interest in a way that captures the important characteristics and relationships**
- **Simulate the resulting market environment and the occasional default of the participants**
- **Calculate the losses resulting from each simulation, and examine these statistics**

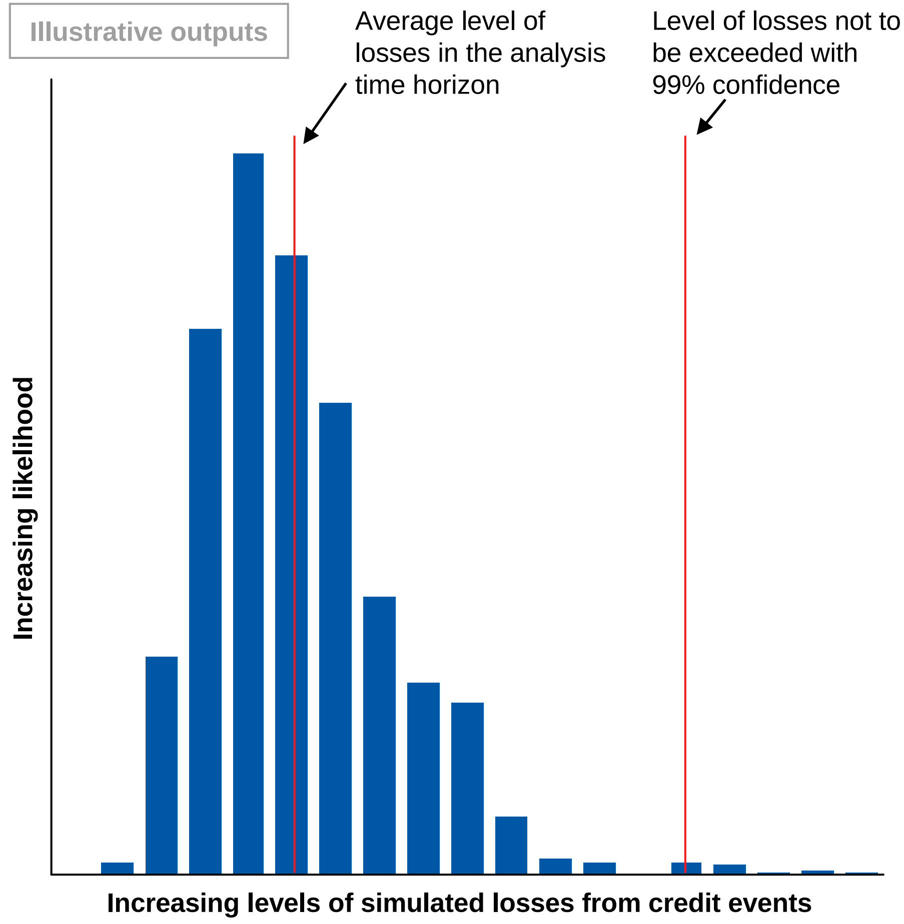
Fundamental credit loss model inputs and outputs

As a tool, the model will illuminate the impact of changes in the inputs on these results

Illustrative inputs

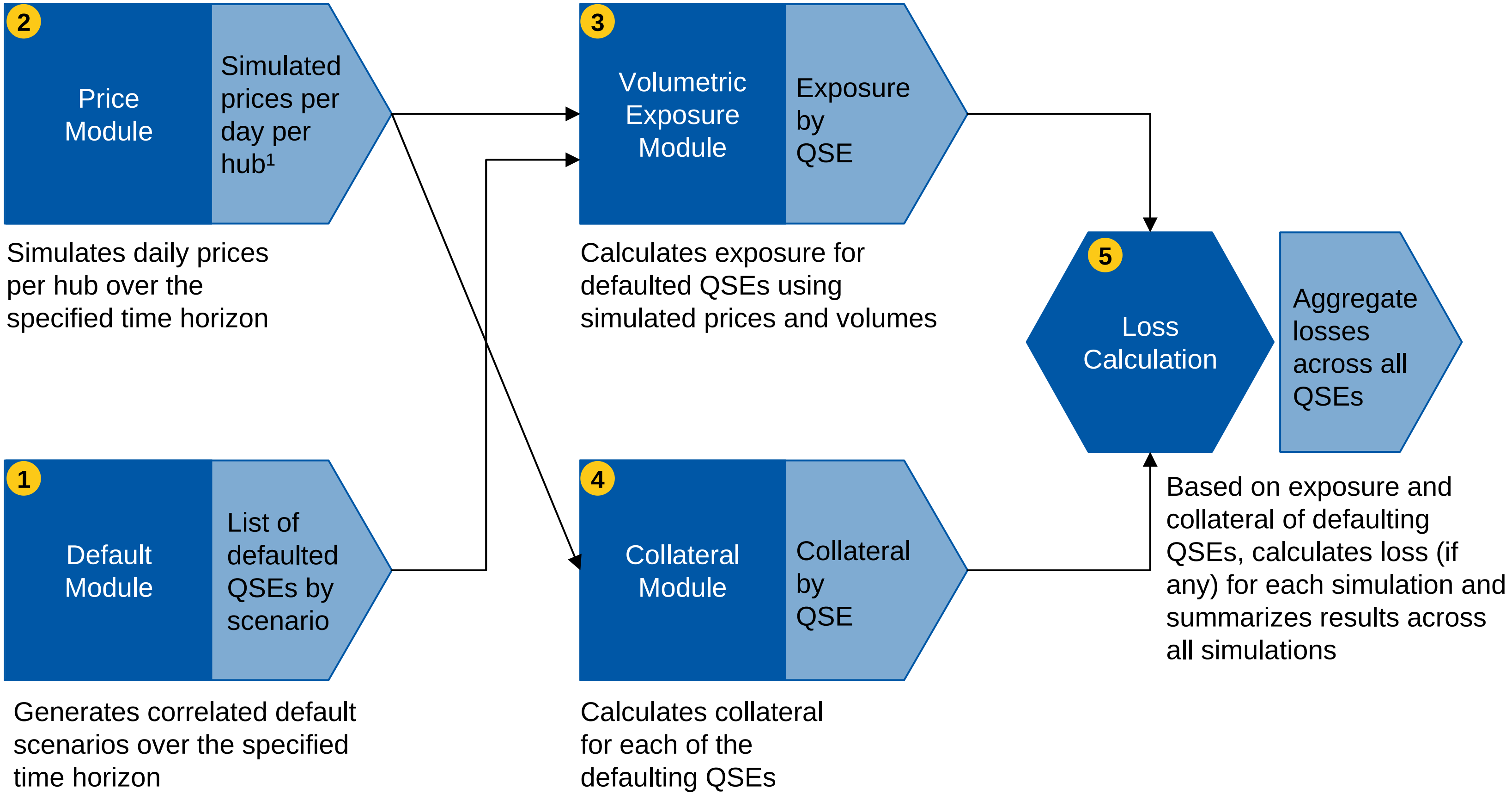
- **Forward prices**
- **Historical volumes**
- **Historical prices**
- **QSE credit ratings (credit scoring model results)**
- **ERCOT collateral rules**
- **ERCOT credit management rules**

Illustrative outputs



Credit Loss Model – High level credit loss calculation configuration

The model consists of four modules: default, price, volumetric exposure and collateral



The model will be run thousands of times in order to estimate a credit loss distribution – this schematic represents one simulation

1. Hub refers to a zone, settlement point, location or market

The model allows the user to make adjustments to inputs and measure how those changes impact the prospective distribution of credit losses

Global inputs

- Time horizon (in days)
- Number of simulations
- Number of hubs/zones
- Number of QSEs

Default module inputs

- Credit score of each QSE (i.e., probability of default)
- Default correlation types
- Market event sensitivity types

Price module inputs

- Price movement correlation between zones
- Forward prices predicted from forward gas prices, based on local spark spreads
- Frequency and size of jumps
- Jump event types (1-, 3-, 6-day jump series)
- Frequency of jumps common to multiple zones
- Differences that drive CRR pricing

Exposure module inputs

- Settlement and billing cycle
- Volume escalation behavior
- Maximum potential volume
- Length of time of mass transition (if applicable)

Collateral module inputs

- Number of days to post collateral and cure a breach
- Simplified collateral calculations
- Collateral haircuts

Key results captured and reported

Overall results	▪ Graphic distribution of losses ▪ Used to assess adequacy of number of simulations, reasonableness of parameters
Central results	▪ Mean loss level; used as an estimate of the expected losses (EL) that are typical of this business environment ▪ Standard deviation of EL, known as the unexpected loss (UL); used to gauge the stability of the EL
Tail results	▪ Specified percentile losses (e.g., 99^{th}%, 95^{th}%); used to examine losses within a given confidence interval and to estimate economic capital requirements ▪ Simulation details for some tail scenarios; used to investigate the loss modes for extreme loss cases

Some key considerations and assumptions in this approach to credit loss modeling

- The model focuses on the volumes potentially withdrawn from the BES (or DAM and RT) markets as the source of potential receivables
- General “types” are assigned to each QSE or counterparty to help characterize their potential behavior (Small Retailer, Large Retailer, Generator, Mixed, Public Power, Trader)
- Defaults are driven solely by randomness and the PDs assigned by the credit scoring model
  - The model draws the random defaults first, then creates random prices and volumes only for those simulations in which one or more defaults occur
- The “Monte Carlo” approach calculates the credit losses based on market prices, participant defaults, volumetric escalation behavior, and the correlation of defaults and market prices
  - Each of these four inputs contains random variables that change for every simulation
  - The credit loss calculation is performed over and over (and over and over) to create one scenario or one credit loss distribution
  - Because the analysis employs random numbers, every analysis will yields slightly different results; how much they change can indicate how stable these results are
- Some key results are defined by confidence levels, or how frequently given thresholds are breached

Some assumptions have been revised based on the Nov 2 CWG discussion

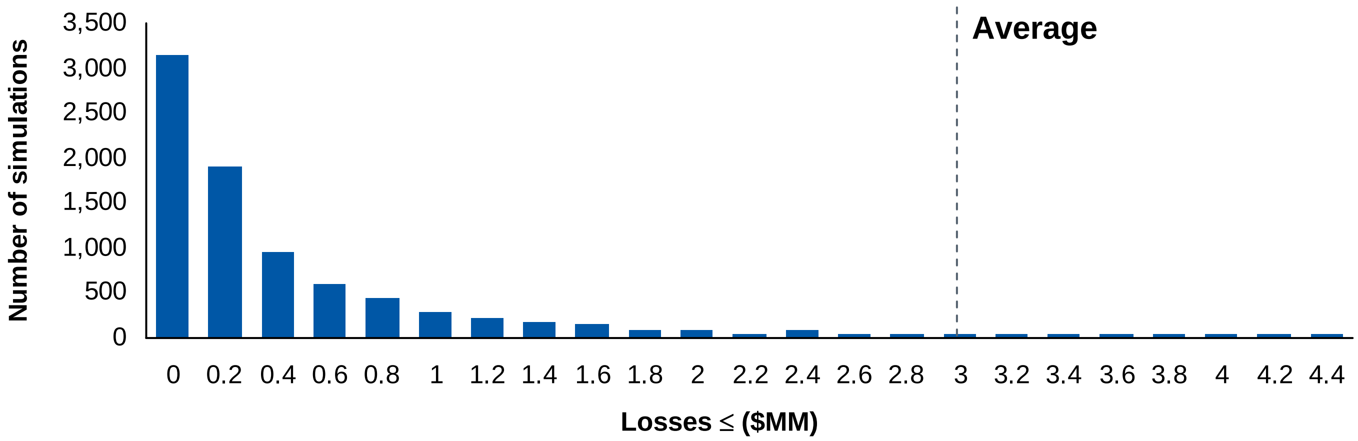
- Volume escalation probabilities in the BES market did not cover the full range of best or worst possibilities
  - Escalation potential was adjusted to reflect the following

	Red to 0	Main Hist	20%	40%	70%	100%
Generators	10%	50%	30%	9%	0%	1%
Sm retailer	5%	20%	40%	10%	0%	25%
All others	0%	50%	40%	9%	0%	1%

- Retail participant default sensitivity to high market prices is hard to predict based on historic load in the ERCOT market, as only a few defaults have taken place
  - Correlation of load serving participant defaults and price spikes was made a uniform 50%
  - Reflects the assumption: If an entity is defaulting in a given period, there would be a 50/50% chance of the default occurring during a price event
- The average size of price jumps was reduced from $120 to $80/MWh, reflecting that most price jumps are expected to be modest while continuing to allow for the possibility of more extreme price events

Confidence levels in Monte Carlo analysis

Example results: Baseline case showing 8,500 of 10,000 simulations



- Histogram shows number of simulations with credit losses less than, or equal, to X MM dollars
- Zero, or rather small, losses are the most common result
  - Almost a third (3,134) of the simulations had no losses; either no defaults or defaults with adequate collateral
  - The results show that 80% of the simulations result in losses that are less than $2,200,000 each (the first 12 bars total 7,993 simulations)
- The average loss across all simulations is about $3 MM
  - Most simulations are well below this, thus a few, rare, loss simulations have much greater losses
  - “Average” is **not** “most common outcome”, but the long run average across all outcomes (the Expected Loss)
- These results are specific to one set of inputs, and one set of simulations
- The pattern shown here is common to virtually every analysis of ERCOT’s market performed to date
  - All have a most common result of zero loss
  - All are heavily skewed to the right, showing only relatively rare, very large losses

Tabular results and comparison for the same Baseline case

- The baseline scenario reflects a combination of market and behavioral assumptions that are easily conceivable for the current market conditions and yields annual losses of
  - $16 MM at the once-in-20-years level
  - $43 MM at the once-in-100-years level
  - $99 MM at the once-in-1,000-years level
- The comparison stress scenario shown uses identical assumptions to the baseline except that all collateral actually held at the beginning of the period is recognized
  - Baseline assumes that all collateral holdings will meet but not exceed ERCOT's required minimums
- 50% of the annual credit losses were less than $194,000
- Most larger loss simulations are the result of several participants defaulting within the one year horizon
- While these estimates represent reasonable estimations of potential losses, actual losses may be more or less than these, as all possible scenarios are not addressed

	Baseline	**Comparison**
Average Loss	2.95	.742
Median	.194	.033
90.0th%	8.26	1.38
95.0th%	15.8	3.96
99.0th%	42.6	10.9
99.9th%	99.8	29.8
Maximum	213.0	156.0
Collateral held	Min. per Protocols	Actual historic

All losses in $ Millions

Economic capital in the ERCOT market

Credit loss impacts on the economic capital requirement is an open question

Corporates and Banks

- Definition of default or insolvency:
  Liab > Assets
- Probability and size of major liability events are estimated using Monte Carlo models
- Level of assets available is a straightforward accounting issue
- Economic capital requirement can be estimated from the potential loss distribution

The ERCOT Market

- Default or insolvency is not easily defined
  - X% of participants or Y % or MW of capacity??
- Probability and size of major liability events are estimated by the credit loss model (like corp or banks)
- Level of assets available is less clear
  - How will each participant respond to a given level of shortpay or uplift?

- The ERCOT market's unique structure does not hold a central pool of capital to provide an economic buffer against credit losses (or any losses)
- Estimating the required size of that pool will require re-thinking what solvency means, and making a number of assumptions about capital availability

- **ERCOT's market flows losses through to it's participants, and the capital held is distributed among them**
- **The level of that capital, its distribution and reliability are largely opaque**

Initial variations examined

Early testing focused on testing model robustness and horizon

- 10,000 simulations were chosen to produce stable results, without taking too much time
  - 2,500 and 5,000 simulations produced stable averages and low percentile losses, but had poor reproducibility at higher (>75%) loss levels
  - 10,000 simulations produced reproducible results up to 99.9% loss levels
  - 20,000 or 30,000 simulations are preferred for higher loss levels, but have 2x and 3x run times
- Horizon of analysis is largely arbitrary, but one year is extremely common in such analyses
  - Because the model scales the PDs, any horizon can be used
  - Longer horizons can tend to exhaust the pool of defaulting counterparties, since no new QSEs are added and defaulted QSE are permanently barred from the market
  - Doubling the time horizon will increase losses at all levels, by less than 2x
  - Many comparative analyses used 6 months, many final results used one year
  - Results are interpreted as credit losses likely to be experienced over the entire horizon

Key Stress Tests – Zonal market design

Many variations in inputs and assumptions have been examined

- Primary stress tests focused on market (price) and participant (escalation and sensitivity) behaviors
- Withdrawal of excess collateral (above ERCOT requirements) prior to default
  - This assumption directly increased net losses
  - Primarily for larger participants, whose defaults tend to drive the tails of the loss distribution
  - Greatly accentuates the impact of all other stress factors
- Ability and likelihood of defaulting participants increasing their exposure to the market toward (or to) their maximal potential (volume escalation)
  - Losses are very sensitive to this parameter choice, since the largest counterparties are orders of magnitude bigger than the smaller counterparties
  - Collateral is based on recent invoicing, thus recent activity rather than potential activity
- Higher prices and/or more, higher and longer duration price spikes
  - Alone, this stress test produced only slightly higher losses
  - In conjunction with enhanced escalation, impact increased noticeably
- Correlation of defaults with price spikes (aka, market event sensitivity)
  - Increasing this correlation increased losses in the loss distribution tails, but not in the extreme tails
  - Extreme tail losses were likely already caused by default on high price days
- Credit quality or rating of the participants
  - Increasing credit quality decreases the number of defaults in any single simulation
  - Also shifts the loss distribution down as there are more cases with no defaults
  - Loss given default is unchanged, although the multiple defaulting entity cases are diminished

Key Stress Tests – Nodal market design

Additional situations should be studied when data become available

- Nodal market design version of the credit loss model differs somewhat from the Zonal market version
  - Both RT and DAM markets can be represented
  - Price modeling at RT and DAM locations is identical to the Zonal BES market model (mean reversion, jumps, correlations, etc)
  - The spirit of the current market rules for collateral have been reflected in the model logic
  - CRR holdings can be accommodated, with valuations for the realized and unrealized portions
- The reasonableness of the overall credit loss results from this model are currently difficult to assess, because there is no firm basis for many of the required assumptions
  - Volume of participation by each counterparty in each DAM and each RT market
  - Price behavior at the DAM and RT locations
  - Number of DAM and RT locations to consider
  - Number, tenor, size and location of the CRRs held by each counterparty
  - Collateral is based on recent invoicing, thus recent activity rather than potential activity
- As data is collected, some of these parameters can be estimated
- Initial model runs can test some of the remaining assumptions, by varying those parameters
- Credit scoring and the estimation of counterparty PDs will be unchanged

Section 4

Next Steps

Next steps for ERCOT in exploring potential credit losses

Near-Term

- Presentation of results to ERCOT Board of Directors on February 19th
- Examine any specific potential loss scenarios suggested by the Finance and Audit Committee and/or the Board
- Continue testing the credit loss models (Zonal and Nodal) to develop a more complete understanding of the interaction of these key parameters
- Conceptualize the means by which ERCOT's current credit controls could fail to provide the necessary collateral to maintain this level of credit loss protection
  - "What-if" scenarios that result in greater credit losses
  - Detailed examination of the very largest loss simulations produced by the model
  - Consideration of how these extreme cases might be prevented or mitigated
- Pursue policy decision on level of acceptable credit exposure

Longer-Term

- Continue collecting nodal price data to parameterize the nodal credit loss model, and assessing potential participant behavior in those markets