OLIVER WYMAN

Corporate Risk

February 6, 2008

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

ERCOT's credit worthiness monitoring & reporting and workout and management practices were found to be very solid. However, in the following areas Ercot fell short of "best practices":

Category	Priority level	Calibration relative to best practice	Status achieved at the end of the project	Initial practice	Progress achieved during this project	Potential next steps
Risk appetite	High			• Some internal discussion in market meetings	• Risk appetite definition should be explicitly defined to better guide ERCOT's risk policies • Estimate credit risk using credit loss model (current OW effort)	• Assess market's comfort level with loss estimates and ability to absorb losses • Board should develop a formal risk appetite statement • Ensure credit policies and procedures are consistent with risk appetite and tolerance
Loss reserve and capital	High			• Some single scenario estimates have been made • Based on historical market circumstances	• Scenarios do not provide a measure of likelihood for the derived loss amount, or the ability to derive multiple loss estimates at different points along the probability spectrum • Credit loss model will provide best practice capability • Credit loss model (OW effort) will estimate loss magnitude	• Use economic capital results to foster discussion regarding risk appetite and a more consistent framework for considering loss reserves

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Exposure measure-ment and monitoring	High			▪ Estimated Aggregate Liability (EAL) and Net Resource Load Imbalance (NLRI) track very recent historical exposure activity ▪ Measurement of forward exposure is based on recent history ▪ Processes are being automated ▪ Response to alerts is rapid and well-defined	▪ EAL and NLRI allow for rapid response to exposure increases ▪ Some discretionary adjustments to exposure in the past have run counter to ERCOT's prudent limits (although ERCOT can adjust exposure up or down) ▪ Forward exposure measurement approach lacks sophistication compared to techniques employing forward price and volume estimates ▪ Credit loss model (OW effort) capabilities may be leveraged to simulate potential future exposure	▪ Forward exposure measurement should be based on forward risk factors (e.g. forward price and volume estimates) ▪ Interim solution may be to calculate NLRI daily
Loss reserve and capital	High			▪ Some single scenario estimates have been made ▪ Based on historical market circumstances	▪ Scenarios do not provide a measure of likelihood for the derived loss amount, or the ability to derive multiple loss estimates at different points along the probability spectrum ▪ Credit loss model will provide best practice capability ▪ Credit loss model (OW effort) will estimate loss magnitude	▪ Use economic capital results to foster discussion regarding risk appetite and a more consistent framework for considering loss reserves

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

Quantitative factors

For example:
Total assets
EBITDA/assets

Quantitative score

Qualitative factors

For example:
Policies and procedures
Management experience

Qualitative score

Blended score

Adjustments

For example:
Warning signals
Guarantor considerations

Probability of default (PD)

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%

▼ 70% weighting   ▼ 30% weighting

Qualitative score

▼

| Improve |
| No impact |
| Deteriorate |

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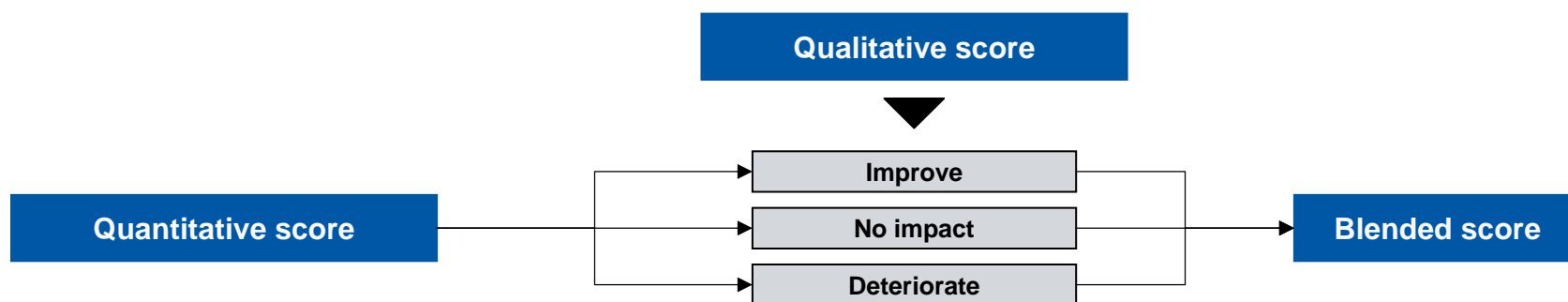
The scoring approach groups output into a rating category with an associated midpoint PD so as not to overestimate precision

Internal credit scoring model

Resulting PD

Example

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
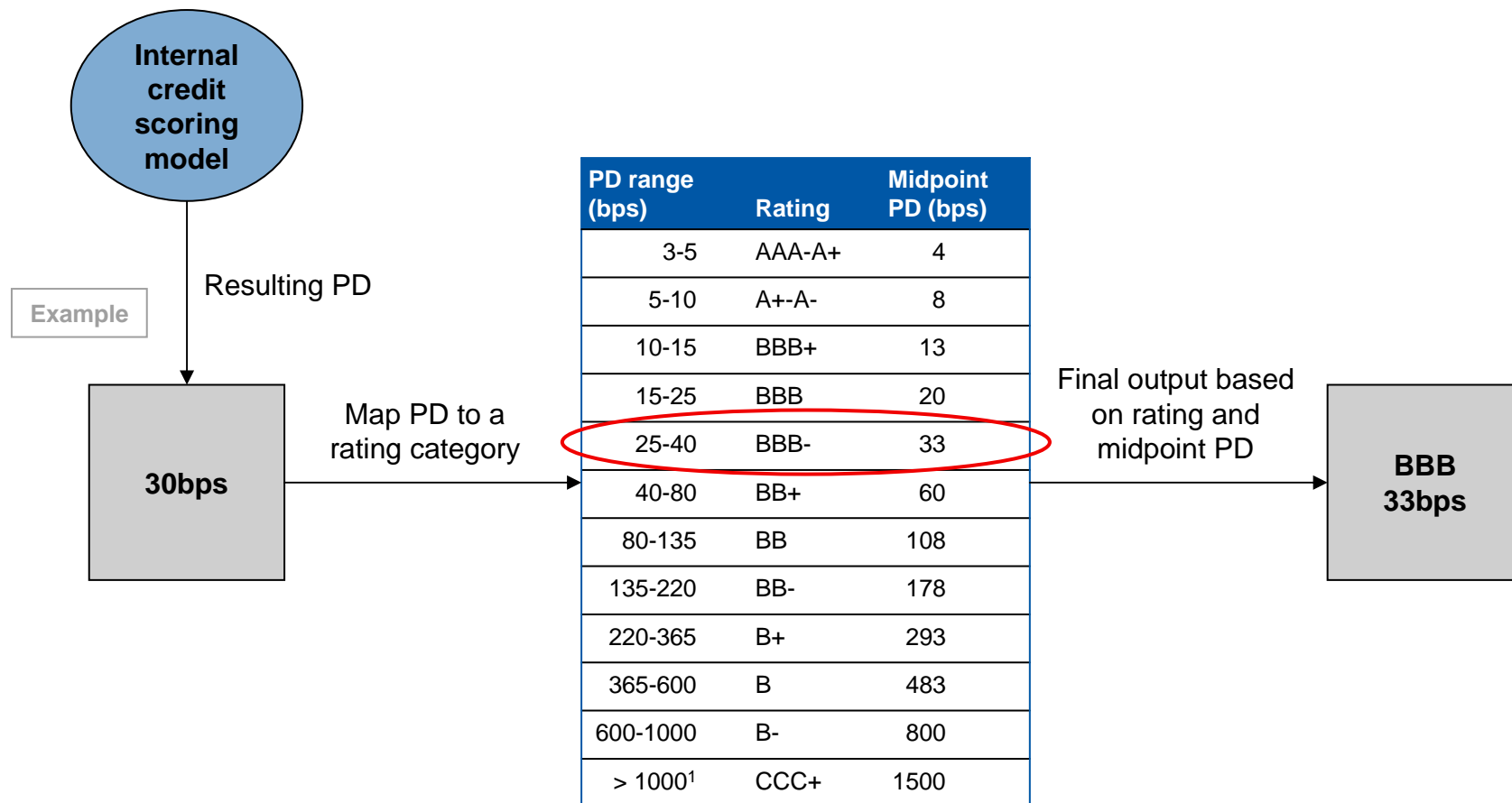
1. All lower PDs map to this rating

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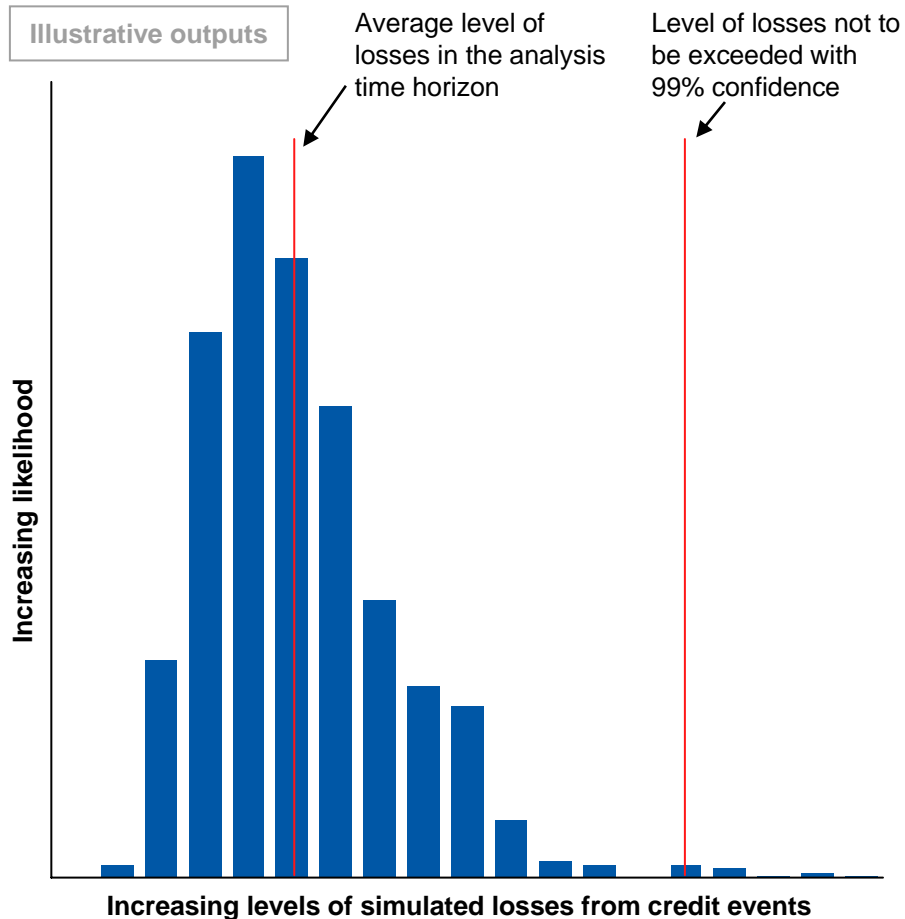
- Forward prices
- Historical volumes
- Historical prices
- QSE credit ratings (credit scoring model results)
- ERCOT collateral rules
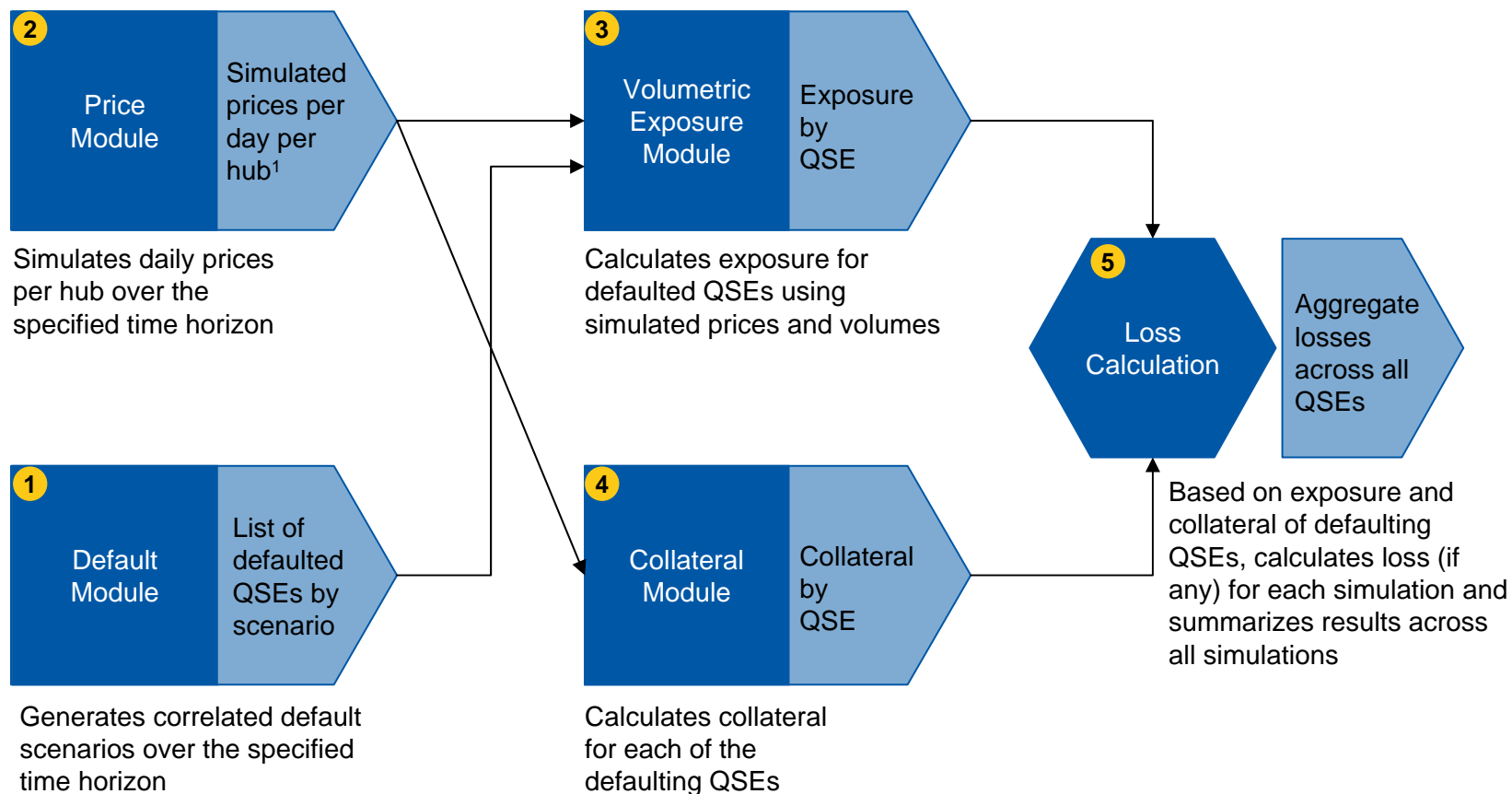- ERCOT credit management rules

Illustrative outputs

Average level of losses in the analysis time horizon

Level of losses not to be exceeded with 99% confidence

Increasing likelihood

Increasing levels of simulated losses from credit events

Credit Loss Model – High level credit loss calculation configuration
The model consists of four modules: default, price, volumetric exposure and collateral

2 Price Module — Simulated prices per day per hub[1]

Simulates daily prices per hub over the specified time horizon

3 Volumetric Exposure Module — Exposure by QSE

Calculates exposure for defaulted QSEs using simulated prices and volumes

5 Loss Calculation — Aggregate losses across all QSEs

Based on exposure and collateral of defaulting QSEs, calculates loss (if any) for each simulation and summarizes results across all simulations

1 Default Module — List of defaulted QSEs by scenario

Generates correlated default scenarios over the specified time horizon

4 Collateral Module — Collateral by QSE

Calculates collateral for each of the defaulting QSEs

> **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., 99th%, 95th%); 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
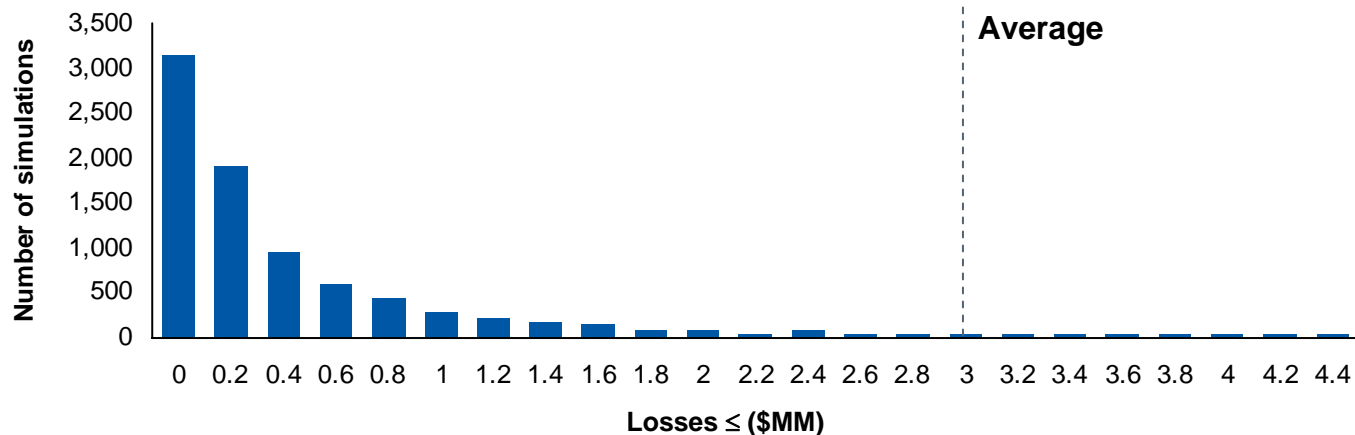
- Histogram shows number of simulations with credit losses less than, or equal, to X MM dollars

- 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

**Overall Project Summary
 and Next Steps**

All of the project's objectives and deliverables have been achieved

Objectives and Deliverables

- Specific project objectives:
  - Review credit practices in ERCOT Protocols, Creditworthiness Standards, and credit risk management practices generally
  - Determine whether ERCOT's practices are consistent with best practices.
  - Provide modeling capability to enable quantification of credit risks for the entire credit portfolio.
  - Estimate Probabilities of Default (PDs) for each participant
  - Estimate the credit loss probability distribution using this model
  - Provide a capital adequacy assessment.

- Deliverables:
  - Evaluation of creditworthiness and credit management practices
  - Credit scoring model and documentation
  - Credit loss model with documentation
  - Loss distributions and capital adequacy evaluation

Next steps for ERCOT in exploring/managing potential credit losses

<u>Near-Term</u>

- 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

<u>Medium and Longer-Term</u>

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

- Use credit loss distribution results to foster discussion regarding risk appetite and a more consistent framework for considering loss reserves

- Board should develop a formal risk appetite statement

- Ensure credit policies and procedures are consistent with risk appetite and tolerance