PV ModuleTech Bankability Rankings: methodology, validation and supplier ratings for Q4'19

Module bankability | Understanding the bankability of module suppliers is a critical aspect of solar project development. Finlay Colville, head of research for PV Tech & Solar Media, presents a model that allows scoring, rating and benchmarking of PV module suppliers by bankability for commercial, industrial and utility segment deployment. Quarterly rankings enable project developers and site investors to shortlist module suppliers when seeking to minimise module supplier risk and maximise site returns over the lifetime of owned assets

Bankability is one of the most critical requirements for PV module suppliers during selection for commercial, industrial and utility (CIU) projects. Until now, the industry has lacked an accepted mechanism to rate suppliers by bankability.

During 2019, the research team at *PV Tech* developed a model using manufacturing and financial data collected over 10 years. The goal was to establish a means of benchmarking any PV module supplier, at any time (quarter), within a 0-10 bankability scoring range, allocated to ranking grades from AAA (highest) to C (lowest).

During August to October 2019, the methodology was explained with a series of articles on *PV-Tech.org* [1], with findings validated against historical and current trends. The first output from the *PV ModuleTech Bankability Rankings* was published during November 2019 [2].

This article summarises the key features of the model, how validation was undertaken, and which companies were revealed as the most bankable suppliers at the end of 2019.

Methodology overview

Investment-risk (or bankability) scores for module suppliers are obtained by combining manufacturing and financial health scores using statistical analysis (nonlinear/power regression), with data dominated by quantitative inputs (six years back, two years forward), and qualitative data kept to a minimum. Validation is done by comparing to sample groupings and how different module suppliers are/were perceived from a bankability standpoint.

The relationship between supplier bankability (B), manufacturing (M) and financial (F) health scores follows a simple nonlinear relationship:

$$B_i = k.M_i^m F_i^n \tag{1}$$

where k is a scaling factor mapping bankability scores to a 0-10 band, m and n are power coefficients, and i is a variable (supplier and time-period specific).

The manufacturing score, M, for suppliers, at any time, is determined by gathering data for each company (annually back to 2013, by quarter to Q1'15), and analysing the dependency of this data on overall bankability. The final manufacturing score is a combination of module supply (shipment), capacity and technology-driven ratios:

$$M_i = a.S_i^p + b.C_i^q + c.T_i^r \tag{2}$$

where a, b, and c are factor-dependent weightings, scaled to generate manufacturing scores for each company by quarter from 0 to 10; S, C and T are shipment, capacity and technology ratios; p, q and r represent power factors.

Manufacturing supply *(S)*

The manufacturing supply factor (S) captures market share by branded module shipments (assembled at company-owned facilities and outsourced/third-party entities).

The analysis identifies each supplier's shipments (*Ship*) by quarter, allocated to six ($j = 1\ldots6$) end-market regions (*Reg*), confined to non-residential (CIU) contributions (*Ship'*), and consolidated using trailing 24 months (*t24m*) of data.

For each company (i), quarterly CIU shipments by region are summed over eight previous quarters (*t24m* at quarter ends), and converted into regional market shares by dividing this by the *t24m* sum of total shipments (CUI specific) in each region,

$$Ship'_i(Reg_j)_{t24m} \Big/ Ship'_{Total}(Reg_j)_{t24m} \tag{3}$$

However, market share in any region is only relevant if strong demand is expected going forward. To address this, two scaling factors are applied. The first considers total future CIU demand (*Dem*) in each of the regions, as a percentage of the overall total global CIU demand, two years out at the end of each quarter or forward-24-months (*f24m*).

The inputs here are among the few qualitative data entries within the analysis, based on forecasted demand (module supply) two years out from any given quarter-

$$Dem'_{Total}(Reg_j)_{f24m} \Big/ Dem'_{Total}(Global)_{f24m} \tag{4}$$

The second introduces end-market risk; critical to understand because policies and demand-related factors create uncertainty. These have a direct impact on the relevance of legacy market-share coverage (shipment volumes). A demand-specific risk factor (*Risk*) is introduced by quarter/region, based on the *f24m* period at any given time:

$$\left\{1 - Risk'_{Total}(Reg_j)_{f24m}\right\} \tag{5}$$

Supply scores are thereby assigned to all suppliers at each quarter-end; for CIU deployment into each of the six regions; based on historic market shares (ratioed against *t24m* global CIU demand) and scaled against future (*f24m*) regional CIU demand and associated demand-risk.

The final score for suppliers (at each quarter-end) is the sum of the scores in each region:

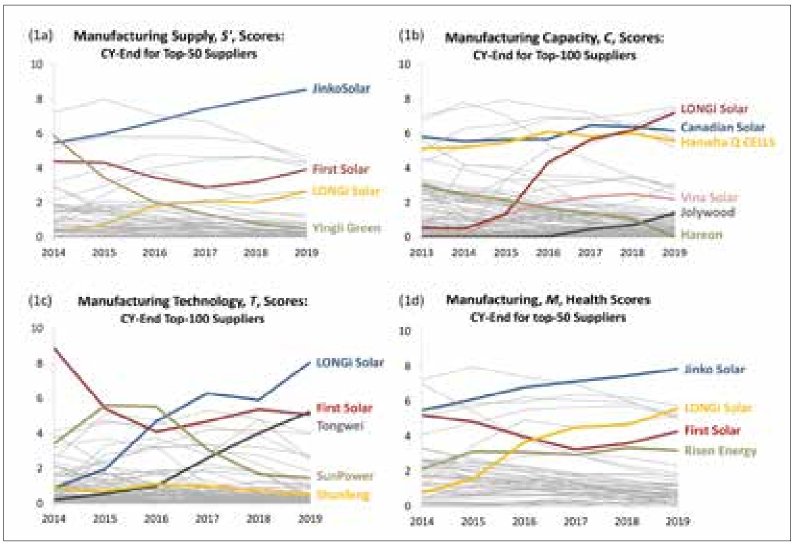


Figure 1. Output from the analysis of PV suppliers across manufacturing health metrics, with examples highlighted for validation purposes

$$S_i' = k_s \sum_{j=1\ldots6}\left[\left\{\frac{Ship_i^t(Reg_j)_{t24m}}{Ship_{Total}^t(Reg_j)_{t24m}}\right\}\cdot\left\{\frac{Dem_{Total}^t(Reg_j)_{f24m}}{Dem_{Total}^t(Global)_{f24m}}\right\}\cdot\left\{1-Risk_{Total}^t(Reg_j)_{f24m}\right\}\right] \quad (6)$$

(6)

The scaling factor *k* assigns scores in 0-10 bands, set quarterly by looking at the distribution of scores and standard deviations. Figure 1a displays sample data output for supply scoring.

Manufacturing capacity

The manufacturing capacity factor (*C*) ranks suppliers by evaluating in-house cell and module quarterly effective capacities across different global manufacturing zones, and factoring in the access these zones have at any given time to global end-markets.

The analysis starts by segmenting each company's effective quarterly cell and module capacities (*Cap*) across eight manufacturing zones ($p = 1\ldots8$): China, Taiwan, India, Japan, Southeast Asia, the US, Europe and Rest-of-the-World.

The next stage determines how much effective in-house cell capacity is available to each module supplier in the zones. This allows differentiation between modules produced by any company (in any zone) using in-house cells (*IHC*) or third-party cells (*TPC*). The resulting module capacity by company (*i*) is:

$$c_1.Cap_i(IHC_p) + c_2.Cap_i(TPC_p) \quad (7)$$

The *c* coefficients are weighting factors depending on whether module capacity uses in-house cells made in the same zone, *Cap*(*IHC*), or by third-party cell producers, *Cap*(*TPC*). This promotes the strength of module suppliers that use in-house cells produced local to module assembly. The weighting factors, *c*, are qualitative, adjusted by quarter and by manufacturing zone, depending on how important in-house vertical integration is.

The next stage introduces the impact of trade (export) restrictions on modules produced within each zone and shipped to any of the six ($j = 1\ldots6$) end-market regions (*Reg*) introduced earlier.

To restate module capacity by company/quarter within the zones, each capacity value (obtained through the summed term above) is multiplied by an end-market 'access-related' factor that is both manufacturing-region and end-market specific. The module sum factor for each supplier is multiplied by a quarterly-variable term based on combining the total quarterly CIU demand (*Dem*') (for each end-market) with a qualitative access percentage term (*Access*) that defines the availability of end-market *j* for module production in zone *p* at any given quarter.

The pro-rated regional contributions for each zone are scaled by dividing by the total global CIU market demand each quarter. The overall scaling factor is:

$$\frac{\sum_{j=1\ldots6}\{Dem_{Total}'(Reg_j).Access_{p,j}\}}{Dem_{Total}'(Global)} \quad (8)$$

This analysis not only adjusts module capacity by manufacturing zone, but also scales the size of the served end-market by the importance of each region, looking at the ratio of the demand (CIU) from that region and the total CIU demand each quarter.

The final capacity score (*C*) for each supplier is the sum of the scores derived from all manufacturing zones by quarter:

$$C_i = k_c \sum_{p=1\ldots8}\left[\left(c_1.Cap_i(IHC_p) + c_2.Cap_i(TPC_p)\right).\left\{\frac{\sum_{j=1\ldots6}\{Dem_{Total}'(Reg_j).Access_{p,j}\}}{Dem_{Total}'(Global)}\right\}\right] \quad (9)$$

where *k* is a variable quarterly scaling factor, to map capacity scores to 0-10, again based on distribution and standard deviation checks by quarter.

The capacity analysis is confined to quarter-only data, not trailing or forward-looking, because capacity strength is an instantaneous variable (has a specific value at any time), dependent on trade-access conditions. Figure 1b displays sample data output for capacity scoring.

Manufacturing technology

The manufacturing technology factor (*T*) ranks suppliers by investments into capital expenditure (capex) and research and development (R&D). For capex, only cell and module stages are extracted by quarter (removing polysilicon, ingot or wafer capex if consolidated).

The analysis starts by isolating total PV manufacturing capex by quarter for each supplier, removing allocations to polysilicon/ingot/wafer, to leave cell/module contributions; *Capex*(*CM*). Weightings are not applied to cell and module because each is generally equally advantageous.

Capex is included across facilities, maintenance, upgrades and new lines. For thin-film, it is necessary to normalise (derate) capex allocations (adjusted annually) due to higher spending compared to c-Si.

For each module supplier (*i*), the respective quarterly cell/module capex values are converted into *t24m* sums because capex by quarter tends to be lumpy.

Capex scores (0-10) for each supplier (by quarter) are found by analysing the data distribution, and normalising each quarter (*u*) for benchmarking. Since capex follows cyclic trending, this promotes investment during downturns.

R&D spending, *R&D*(*PV*), follows similar methodology to capex, but excludes only polysilicon. Quarterly spending is assigned to each supplier, with *t24m* values at quarter-ends, and scores are converted to 0-10 based on normalisation each quarter (*v*). Again, R&D investment during downturns is emphasised.

To establish technology-based quarterly scores (*T*) by module supplier (*i*) for any quarter, the two scores (capex, R&D) are combined by applying weightings (prioritised to capex), denoted by the *t* coefficients below. The final step is to normalise each quarter to 0-10 through quarterly coefficients *k*, yielding:

$$T_i = k_t.\{t_1.u.Capex_i(CM)_{t24m} + t_2.v.R\&D_i(PV)_{t24m}\}$$

(10)

Figure 1c displays sample data output for technology scoring.

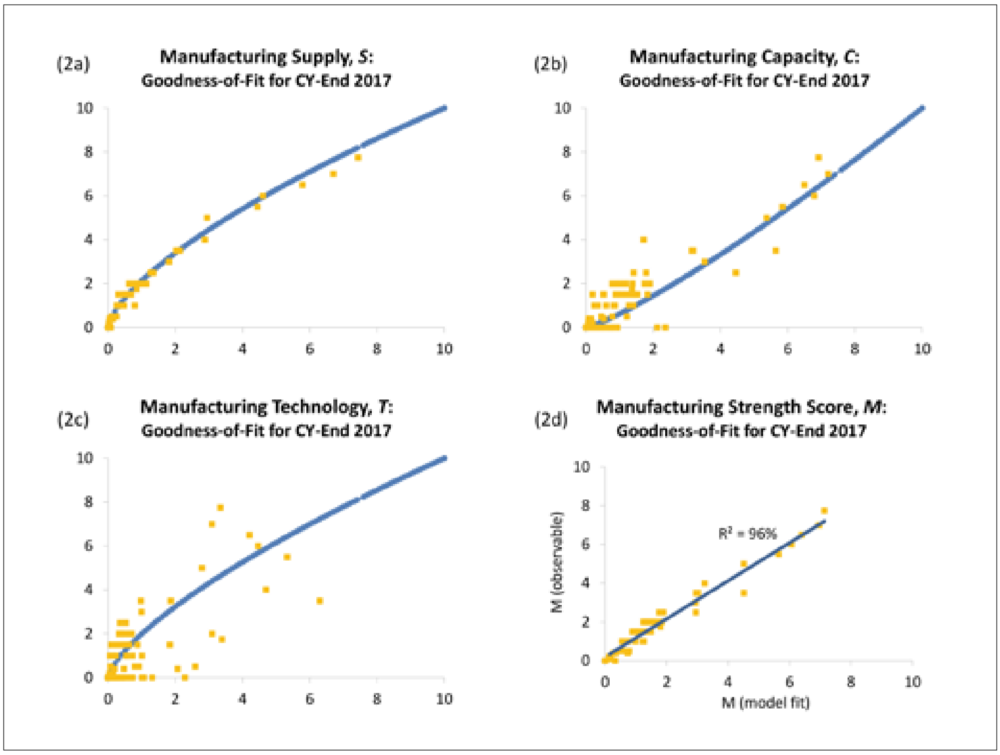


Figure 2. Validation of the manufacturing analysis, including the dependency of supply, capacity and technology variables, and the overall fit to module suppliers' historic (observable) bankability status

Manufacturing strength

Manufacturing strength (*M*) considers the dependence of the three manufacturing variables as given by Equation (2). To understand the dependence of *S*, *C* and *T*, it is useful to compare with final model accuracy (goodness-of-fit); see Figures 2a to 2c. For each graph, the values of *S*, *C* and *T* are plotted (*x*-axis) against the original qualitative entries for each company's *M* scores (*y*-axis), with the sold line-fit based on the final terms $a.S^p$, $b.C^q$, and $c.T^r$, scaled to 0-10. The closer the scatter points to the line-fit, the stronger the dependence.

The profiles of the curves, in each of the *S*, *C*, and *T* plots, drives power factor determination for the variables. Coefficients are determined by combining the power dependency of each variable with the corresponding data fit accuracy and 0-10 scaling. The coefficients and power factors yield the overall weightings for *S*, *C*, and *T*.

Figure 2d provides a final check on the analysis (validation). The fit between the original qualitative *M* values (observable, *y*-axis) should be as close to a 1:1 linear fit, when calculating *M* using the modelled equation (all coefficients and factors determined), plotted on the *x*-axis. Figure 1d displays sample data output for manufacturing scoring.

Financial strength (F)

When benchmarking financial health of suppliers, a technique routinely applied is a model developed by Altman [3] as a measure of financial distress relative to potential bankruptcy. Despite a lack of checks on this scoring system relative to historical performance of PV companies, it remains a valid means of assessing 'financial strength' (least likely to go bankrupt). It is easy to generate Altman Z Scores for suppliers (or corporate holding entities): the challenge is how to interpret and understand them in context.

The approach applied here retains the integrity of the Altman model, but adapts the scores for correlation to PV. This involves two steps, starting from Altman Z Scores and ending up with new financial health scores (*F*) that rank companies 0-10 across new zones (score bands), validated with data observed in the sector.

The first stage involves gathering Altman Z Scores for suppliers or parent companies (warranty 'guarantors'). This uses quarterly-reported information, as opposed to annual information only. (The inclusion of privately held entities is discussed later.)

This is where traditional approaches have stopped, categorising Z Scores of PV companies within legacy Altman zones. However, typically more than half of top-20 suppliers (at any given time in the past decade) have scored at levels suggesting imminent bankruptcy.

Therefore, new Altman Z Score limits are established, representing 10-year upper/lower values of module suppliers, shown in the centre image of Figure 3 by the terms Best-in-Class (*PV-BiC*) for the upper, and Technically Bankrupt (*PV-TB*) for the lower. *PV-TB* can be viewed as a point of 'no-return' in PV, often referred to as 'zombie' modus-operandi.

Next, it is necessary to adjust Altman bands (safety, grey, distress) to new ones. The model retains three-level traffic-light coding (green, amber, red), renamed Comfort Zone (green), Zone-of-Uncertainty (amber), and Distressed Zone (red). Suppliers in the Zone-of-Uncertainty can recover operations (move to Comfort Zone) or descend rapidly (becoming 'unbankable').

The next step involves assigning PV financial scores (*F*) in a 0-10 band, where

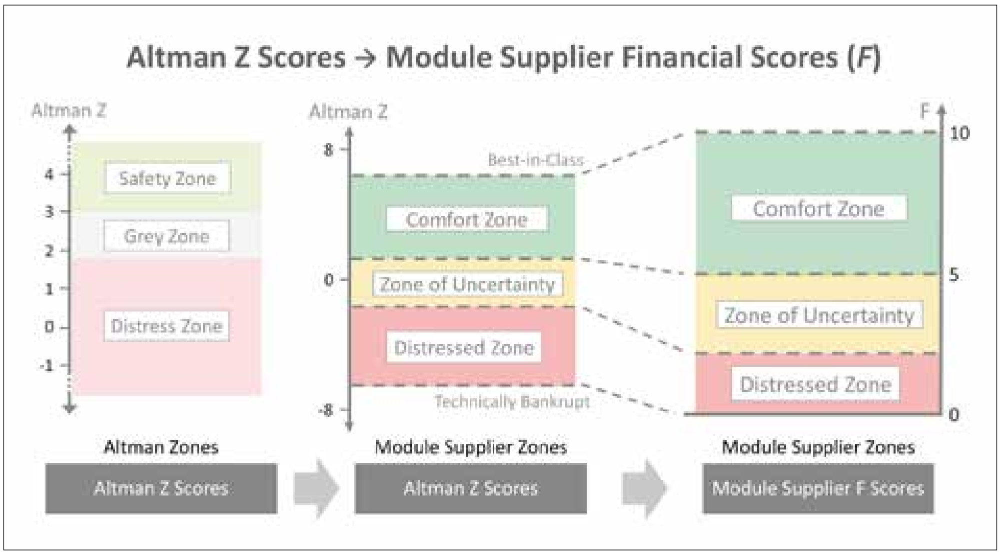


Figure 3. Schematic illustration of restating financial operating zones for PV module suppliers, with a new mapping function to assign financial health scores within a 0-10 range

scores above 5 (or 50%) fall into the Comfort Zone. Mapping Altman Z Scores (labelled

$$F_i = 0, if\ A_i \leq A_{PV-TB} \quad (11a)$$

$$F_i = \beta_0 + \beta_1 A_i + \beta_2 A_i^2 + \cdots + \beta_n A_i^n, if\ A_{PV-TB} < A_i < A_{PV-BIC} \quad (11b)$$

$$F_i = 10, if\ A_i \geq A_{PV-BIC} \quad (11c)$$

The key term, shown by Equation (11b), involves mapping using a polynomial of order *n* (coefficients given by β terms). The best-fit solution is determined by approximating upper and lower values of *F* (10 and 0) to successive local minima/maxima, mapping the boundary data sets (distressed/uncertainty and uncertainty/comfort), and reducing to a set of simultaneous equations.

A final correction deals with one-off accounting issues and smooths out seasonal lumpiness, by using trailing twelve months (*ttm*) averages.

Bankability strength (B)

The bankability strength (*B*) relationship is relatively intuitive, directly scaling the manufacturing (*M*) and financial (*F*) values; see Equation (1). To be bankable, suppliers must have manufacturing strength and demonstrated financial health status at the same time. The challenge is to identify the scaling constant (*k*) and power factors (*m* and *n*); and validate with sector activity.

This is done by comparing the output to actual supplier standings (observables), based on various suppliers in the past, in addition to the current landscape. The solution starts by considering anchor points of the bankability, *B*, scoring band; from lowest bankability score (0) to highest (10). The lower bound is self-explanatory:

$$B_{min} = 0, if\ M = 0\ or\ F = 0 \quad (12)$$

The conditions governing the upper band are more complicated. In theory, one would expect maximum bankability score

$$B_{max} = 10\ if \begin{cases} M = 10 \\ F = 10 \end{cases} \quad (13)$$

While theoretically possible, it is practically unattainable. If the coefficients are set using this boundary condition, then few (if any) suppliers achieve bankability scores above 50%.

This anomaly is resolved by removing one-off outliers (extreme values) in the datasets for *M* and *F* scores, and introducing percentiles with the maximum value of *B* now given by:

$$B_{max} = 10\ if \begin{cases} M = M_v\left(P_m, (N_m)_{t3y}\right) \\ F = F_v\left(P_f, (N_f)_{t3y}\right) \end{cases} \quad (14)$$

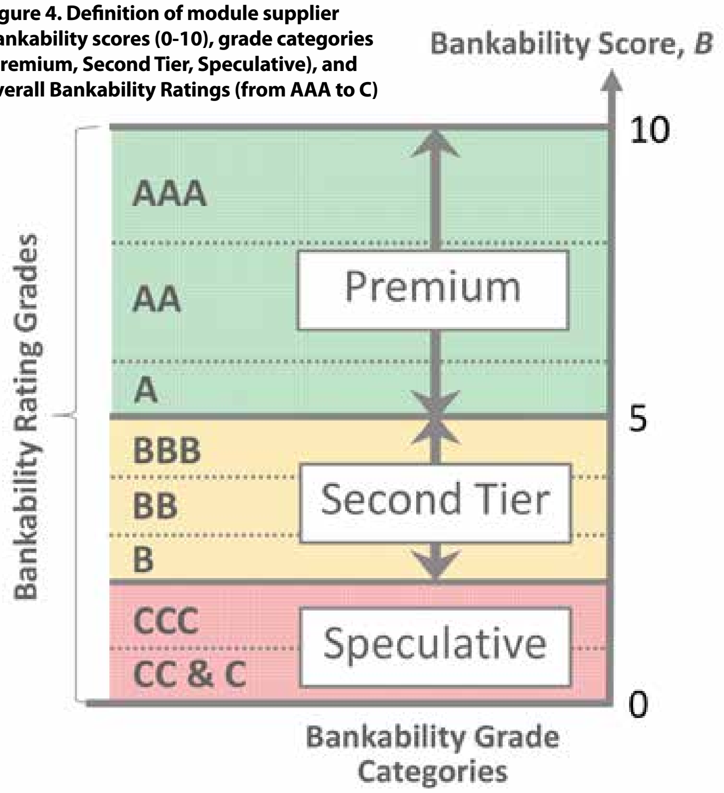
Here, M_v and F_v are percentile values of *M* and *F* across a total of N_m and N_f data entries over a trailing three-year period (*t3y*), and P_m and P_f are input percentiles for *M* and *F*.

The final step is to set the ratio of the power coefficients, *n* and *m*. The solution is achieved by recognising that financial health is more important than manufacturing health. The solution to *k* is:

$$k = {B_{max}}/{(F_v^n . M_v^m)} \quad (15)$$

Bankability scores (0 lowest, 10 highest) are assigned to three grade categories: Premium, Second-Tier, and Speculative. Suppliers with scores in the range 5-10 are placed in the highest (Premium); in contrast, lowest performers (scoring 0 to 2) are in the Speculative grade. Each grade has three rankings/ratings (e.g. Premium includes AAA, AA, and A), shown in Figure 4.

Figure 4. Definition of module supplier bankability scores (0-10), grade categories (Premium, Second Tier, Speculative), and overall Bankability Ratings (from AAA to C)



Privately held companies

There is no widely accepted means of benchmarking public and privately held module suppliers. To address this, the route chosen [4] was to derive a practical/approximate variant, guided by two themes: equate with the public-listed Altman ratio-discriminant model; choose inputs that can be realistically obtained from privately held suppliers (or parent entities).

There is an Altman equivalent for privately held companies [5]. It retains the concept of summing terms based on liquidity, leverage, profitability, solvency and activity, but replaces working capital and market capitalisation entries with alternate numbers/terms. It requires eight accounting terms to be known (compared to the listed version based on seven). It creates different scoring values/zones, making benchmarking challenging.

To address this, a modification of the public-listed Altman equation was developed, reducing the terms/ratios to a minimum, while keeping error bounds on final financial scores within acceptable bounds. This allowed decoupling the market-cap issue, and not seeking an equivalent value for private companies (such as book value of equity).

This was done by examining Altman Z scores derived for listed PV module suppliers (or parent entities), and identifying the significance of the constituent terms, considering actual data that could be expected from private companies in practice.

In looking at module suppliers (and parent entities) that are publicly listed, there is a range of business models. To establish a shortcut to reaching financial strength scores, it was necessary to form test groups where chosen companies operate with similar characteristics.

With the goal at +/-10% equivalence to scoring generated from the initial five-ratio Altman Z approach, the number of ratios could be reduced from five to three for each test group. The coefficients for the

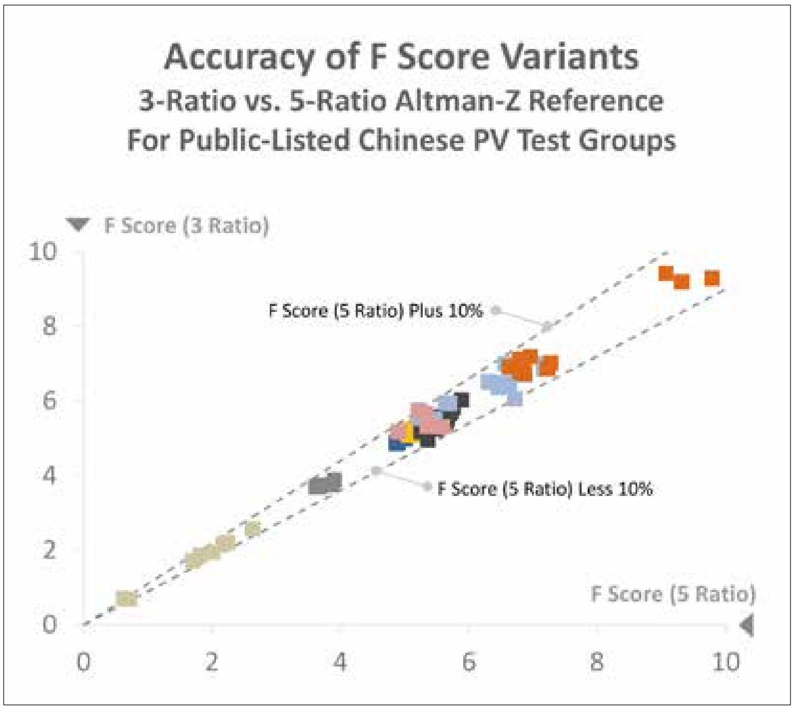


Figure 5. Accuracy of the new three-ratio reduced-Altman method, compared to the full five-ratio version applied to public-listed suppliers. Privately-held entities are scored using the three-ratio model valid for the peer-group each is assigned to

three chosen ratios (noting that a scaling constant is essential now) were determined using a least-squares linear regression analysis, where the 'residual' is the difference between the original five-ratio Altman and the new reduced three-ratio approach.

To test the validity of the new approach, the level of accuracy for the reduced-fit model can be assessed when applied to a known dataset (public-listed PV module suppliers/parent-companies); see Figure 5. The original (full-analysis) Altman Z scores going back 3-4 years for each company, converted to the 0-10 (*F*) scoring band as explained before, are on the *x*-axis; the equivalent 0-10 financial scores, using the new shortened variant, on the *y*-axis. The match of the shortened variant with the original Z score value is the test of the approach validity.

This is visualised in Figure 5, where a 1:1 line-fit would represent 100% accuracy. Shown are two dashed straight lines above and below 1:1 fitting, with upper/lower bounds at +/-10% accuracy.

Supplier rankings for Q4'19

The first release (Q4'19) of the *PV ModuleTech Bankability Rankings* report revealed exclusive status for four suppliers (JinkoSolar, LONGi Solar, Canadian Solar and First Solar), as the only companies with AA-Rating. No companies scored in the AAA-Rated band.

The Q4'19 report release from *PV Tech* contains in-depth company-specific analysis across key manufacturing and financial metrics forecasted to the end of 2020, for A and B ranked suppliers. The pyramid chart in Figure 6 displays the output hierarchy showing all A and B grade listings.

To be AA-Rated (or indeed AAA), companies need 10GW-plus CIU annual shipments coupled with moderate-to-good finances, or 5-10GW shipments (CIU) with strong finances. This explains why only a few companies are AA-Rated today, with the absence of AAA ratings also a consequence of low margins inherent to module sales.

Final discussion

The strength of the model developed to rank and benchmark module suppliers by bankability for CIU selection will be further validated by reviewing changes observed across the various rating bands over time. The first output from the Q4'19 dataset appears to suggest a very good match to the companies winning large-scale global supply business in 2019.

Since the model is comprised of a wealth of in-house and external factors important to manufacturing and financial health, the ability to forecast company-specific bankability one to two years out could become a highly sought after extension, in particular for supplier selection in large-scale projects that have multi-phase delivery schedules. During 2020, the model will be extended to allow for this option. ■

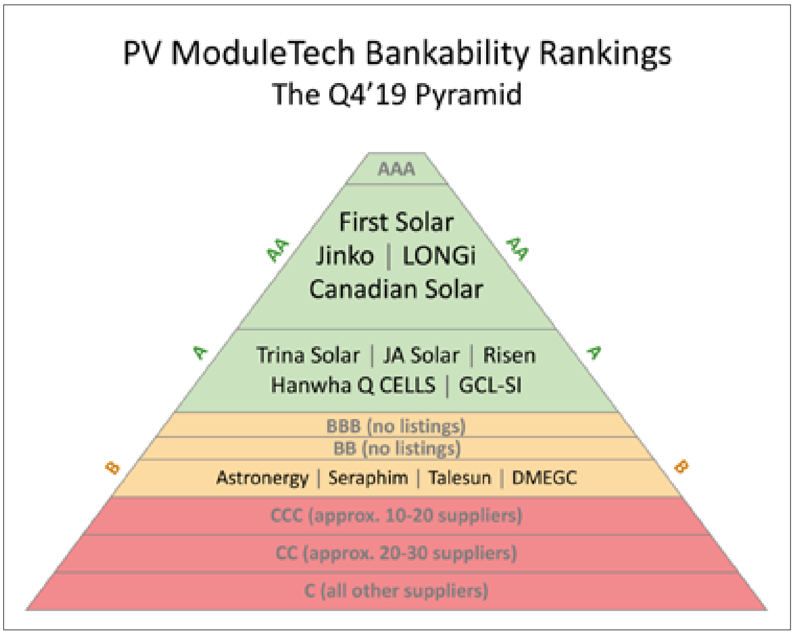


Figure 6. The PV ModuleTech Bankability Rankings pyramid for Q4'19, showing four suppliers having industry-leading AA-Rating status

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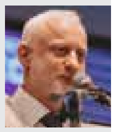

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