Online Supplement for Supplier Sustainability Assessments in Total-Cost Auctions

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I. Implementation of sustainability assessments in total-cost auctions in practice

Through our discussions with our industry partner EcoVadis (a leading supplier sustainability assessment firm) we learned that their clients (buyer firms) use a total cost of ownership approach to sustainable procurement when selecting a supplier. Our paper is motivated by this observation. We have followed EcoVadis's operations closely over the years and had many interactions (in fact, one of the authors is on their scientific advisory board). Thanks to these interactions, our paper closely reflects the industry practice, and provides a rather accurate modeling of the procurement process at EcoVadis's client firms (buyers).

Supplier sustainability assessments require deep domain expertise. EcoVadis employs technical analysts to provide supplier sustainability ratings to buyer firms of 150 commodities by collecting information from more than 300 qualified sources, and evaluating 21 corporate social responsibility criteria including water, biodiversity, local pollution levels, chemicals & waste, product use, product end of life, customer health and safety, second-tier supplier evaluations, and so on (EcoVadis(a) 2018). After the assessment process, EcoVadis assigns a sustainability rating to the supplier (a score out of 100). In many cases, the suppliers themselves lack the technical capability, in-house expertise, and information needed to assess and quantify their rating. Hence, unlike many other supplier quality dimensions, without proper assessments the sustainability ratings are unobservable to any party to start with. Furthermore, in contrast to many other quality dimensions that the suppliers can adjust in order to win a buyer's business, they cannot change their sustainability ratings in the buyer's imminent contract term. Being unobservable to any party without assessments and its rigid nature renders sustainability **non-biddable**. This is one of the reasons why supplier sustainability is different from biddable supplier quality dimensions, and requires further attention in the context of a competitive-bid process.

EcoVadis reports that their clients (buyer firms) use a weighted total-cost ranking approach in their procurement auctions (which is in line with ISO20400 Sustainable Procurement Guidance, ISO (2017), see page 26) by converting sustainability ratings into unsustainability cost markup terms (by using a cost-multiplier) which are then added on to the price bids of the respective suppliers:

"*The sustainability rating of suppliers can be integrated into different procurement processes. As it is a score out of 100, it makes it easy for procurement professionals to use as an objective, quantifiable metric. For example, in a RFP/tender, it can be used as a weighted percentage of the overall award decision.*" EcoVadis(b) (2018)

Various United Nations sustainable procurement resources document a similar approach to supplier selection:

"*The evaluation process must provide a fair, transparent and accountable method for assessing supplier bids on the basis of balancing cost with sustainability and other non-financial factors.*" UN (2017)

"*The evaluation and contracting stage makes use of the standard evaluation methods; however, it should place specific emphasis on use of weighted and ranked criteria incorporating the specific performance criteria and specifications that address sustainable procurement factors.*" UN (2017)

"*The total points assigned for sustainability criteria have to be weighed against other possible criteria and price. For an ambitious approach to sustainability, it is recommended that sustainability criteria account for* 20% *of the weight compared to price.*" UNEP (2011)

The weighted total-cost ranking approach described above is called a "Total-Cost Auction" in the procurement auction literature. As evidenced above, if they choose to make a more informed supplier selection decision taking into account the supplier sustainability levels and the associated cost of ownership, the buyer firms need to first use costly supplier assessments to evaluate the cost markups. To summarize, in practice (also as modeled in our paper), the sequence of events linking supplier sustainability assessments with total-cost auctions is as follows:

1. Buyer firm provides a list of suppliers to assess to Ecovadis.
2. EcoVadis conducts sustainability assessments on all supplier on the buyer's list, and evaluates the sustainability ratings.
3. Buyer uses Ecovadis' assessments to create an additive bid markup for each supplier.
4. Buyer holds a total-cost auction in a format of her choice. Ecovadis reports that the buyers often use sealed-bid or open-bid formats, which is in line with Beall et al. (2003) which shows these are the two most common formats.

Further details on EcoVadis can be found at www.ecovadis.com.

II. Sealed and open-bid formats

In the sealed-bid format, suppliers submit their best and final bid only once. The buyer adds the cost markups (if using assessments, mean cost markup if not) to the price bids to create the total-cost scores. Suppliers cannot observe their competitors' bids or the cost markups, and use their prior beliefs on others' total-costs in structuring their own bids. Where needed to avoid confusion, we refer to a random variable associated with a realized value by using a capital letter. As given in Kostamis et al. (2009), bidding with cost markups in a sealed-bid auction takes the form of a symmetric, first-price reverse auction such that supplier i's bid $p_i^{(a)}$ given δ_i, is $p_i^{(a)} = c_i + \frac{\int_{c_i+\delta_i}^{c_0} (1-\Gamma_a(t))^{N-1} dt}{(1-\Gamma_a(c_i+\delta_i))^{N-1}}$, where Γ_a is the total cost distribution with assessments. Without assessments, supplier i bids $p_i = c_i + \frac{\int_{c_i+\mu_\Delta}^{c_0} (1-\Gamma(t))^{N-1} dt}{(1-\Gamma(c_i+\mu_\Delta))^{N-1}}$, where Γ is the total cost distribution without assessments. The expected assessment value under sealed-bid auction is $EAV_S = E_{\mathbf{p}}[\min\{p_{1:N} + \mu_\Delta, c_0\}] - E_{\mathbf{p^{(a)}},\mathbf{\Delta}}[\min\{(p^{(a)} + \Delta)_{1:N}, c_0\}]$.

In the open-bid format, suppliers bid their prices, and the buyer converts them to total-cost scores (with cost markups added on top of price bids if using assessments, mean cost markup if not). Since the auction is open, the suppliers can observe each others' total-cost scores and can repeatedly lower their bids with this information. Suppliers stay in the open-bid auction until winning or reaching their production cost. The auction ends when there is only one supplier left, and this remaining supplier wins the auction. With independent production costs and cost markups, as in our setting, it is a weakly dominant strategy for suppliers to bid down to their true production costs before dropping out (see for example, Kostamis et al. (2009) and Krishna (2010)). Then, the buyer's expected total cost is the second-lowest total cost or the outside option, whichever is smaller. The expected assessment value under the open-bid auction is $EAV_O = E_{\mathbf{c}}[\min\{C_{2:N} + \mu_\Delta, c_0\}] - E_{\mathbf{c},\boldsymbol{\Delta}}[\min\{(C+\Delta)_{2:N}, c_0\}]$.

III. Limiting the number of assessments on an ex ante asymmetric supply base

We now consider the possibility that the buyer faces an ex ante asymmetric supply base. This asymmetry may be due to directly observable characteristics (e.g., having suppliers in two different countries with different sustainability legislations), or may be easily identifiable by the buyer using a Request for Information stage [1] (e.g., suppliers with and without waste water treatment facilities).

Facing two ex ante asymmetric supplier pools, the buyer can then use a costly assessment to learn more (e.g., how effective the supplier's water treatment actually is). As we will see below, observing the asymmetry across the two supplier pools, the buyer can fine-tune her assessment policy to strategically limit the total number of suppliers to assess (and hence the assessment cost).

We define supplier categories $\tau = A$ and $\tau = B$ to reflect the asymmetry between two groups of suppliers A and B, respectively (e.g., suppliers which have waste water treatment facilities and those which do not). Supplier i's production cost has two additive components $c(\tau_i) + \epsilon_i^c$. Random variable ϵ_i^c follows cumulative distribution function G, satisfying the standard regularity condition that $\epsilon_i^c + \frac{G(\epsilon_i^c)}{g(\epsilon_i^c)}$ is strictly increasing. The structural form of $c(\cdot)$ which maps the supplier category to a deterministic, non-negative, and additive production cost term is publicly known, but both ϵ_i^c and his category τ_i is supplier i's private information.

Similarly, the cost markup associated with supplier i is comprised of two terms: $\Delta(\tau_i) + \epsilon_i^\Delta$. Supplier categories and the structural form of $\Delta(\cdot)$ (which is deterministic and non-negative) is publicly known.

[1] See the Online Supplement Part IV below for a formal model of a procurement process with a Request for Information stage that results in a setting with ex ante asymmetric suppliers like the one in this subsection.

Neither the buyer nor the supplier can readily observe ϵ_i^{Δ} without assessments (this is because, as explained in §1 of the main text, the suppliers cannot quantify the precise cost markups). ϵ_i^{Δ} is a random variable symmetrically distributed around its finite mean $\mu_{\epsilon^{\Delta}}$ with cumulative distribution function F. We denote by $\Lambda^{(\tau_i)}$ the deterministic base-cost (i.e., $c(\tau_i) + \Delta(\tau_i)$) for supplier i.

To summarize, both the buyer and the supplier i observe τ_i (e.g., whether the supplier he has a waste water treatment facility or not), and supplier i privately knows its additional production cost term ϵ_i^c. But assessments are needed to observe ϵ_i^{Δ} (e.g., how effective the waste water treatment facility actually is at protecting sensitive downstream wetlands).

We define *EAV*(M_A, M_B) as the expected assessment value when the buyer assesses $M_A \in \{0, N_A\}$ category-A and $M_B \in \{0, N_B\}$ category-B suppliers, respectively. Let category-A denote the supply base with the lower total base-cost, i.e., $c(A) + \Delta(A) \leq c(B) + \Delta(B)$. Proposition 5 characterizes the buyer's optimal assessment policy.

PROPOSITION 5. *The buyer assesses a category-B supplier only if she also assesses all category-A suppliers. The buyer's optimal supplier assessment policy is as follows: Assess none if EAV*$(1,0) < K(1)$*, assess all if EAV*$(N_A, N_B) \geq K(N_A + N_B)$*. Otherwise, if EAV*$(N_A, 0) \leq K(N_A)$*, assess* M^* *category-A suppliers where* M^* *is the lowest integer such that EAV*$(M^*+1, 0)-$ *EAV*$(M^*, 0) \leq K(M^*+1) - K(M^*)$*. If EAV*$(N_A, 0) > K(N_A)$*, assess all category-A suppliers and* $M^* - N_A$ *category-B suppliers where* M^* *is the lowest integer such that EAV*$(N_A, M^* - N_A + 1)-$ *EAV*$(N_A, M^* - N_A) \leq K(M^*+1) - K(M^*)$*.*

Facing two ex-ante asymmetrical supplier pools (e.g., with and without waste water treatment facilities, or in two different countries with different sustainability legislations), a procurement manager may intuitively think that she should use supplier assessments on the supplier pool with higher average cost markups (e.g., in the less sustainable pool). But, Proposition 5 shows that when deciding on which additional supplier to assess, the buyer should prioritize the supplier category with the lower total base-cost which may indeed be the supplier pool with lower average cost markups. Hence, the buyers can account for any ex ante asymmetries across suppliers, and adjust their assessment policy accordingly.

IV. Using an RFI prior to assessments

In Part III above we analyze a setting where the buyer faces an ex ante asymmetric supply base. When this asymmetry exists but may not be directly observable, buyers, in many practical real-life settings, request credible, certified, and documented information from suppliers during a Request for Information (RFI) stage (prior to the auction and the assessment step). For example, in the sustainable procurement context, buyers may request information on suppliers' production technologies which are linked to the sustainability levels. Suppliers report the relevant information (e.g., certified/credible information on the existence of a water treatment facility if they have one, or simply the lack of it) in response to the buyer's RFI in order to be able to bid in the subsequent auction process.

In the RFI stage the buyer requests credible/certified information on τ_i which she can also verify with assessments.[2] Observing the supplier categories, the buyer then decides whether to use the supplier assessments. Finally, the buyer runs an optimal total-cost procurement auction. Hence, the timeline with an RFI is as follows:

1. For each supplier i, nature chooses τ_i, the supplier's category, and reveals it to the supplier. Nature also chooses ϵ_i^c and $\epsilon_i^\triangle$, and reveals ϵ_i^c to supplier i, while neither party can observe $\epsilon_i^\triangle$ without supplier i undergoing an assessment.
2. Each supplier i truthfully reports to the buyer his category τ_i during the RFI stage.
3. The buyer conducts assessments (if any) in order to further assess the suppliers (to learn the $\epsilon_i^\triangle$'s).

[2] Assessments allow the buyer to verify the supplier's category τ_i, and this has an important implication for a powerful principal, like the buyer we study in this paper. It gives the buyer the ability to ex post verify information that she could ask a supplier i to divulge, namely τ_i. This can be used to induce suppliers to truthfully report their categories. The logic behind this is simple: If the principal (the buyer) discovers the agent (the supplier) has misrepresented his category, the principal will severely punish the agent (e.g., commit to never do business with the supplier again or badly damage the supplier's reputation by widely revealing their misrepresentation). A summary on an agent's incentives for truthful disclosure of ex post verifiable information under the possibility of random assessments and sanctions in a principle-agent setting can be found in Laffont and Martimort (2009) (pg. 125), tracing back to the seminal paper Becker (1968). Since our powerful buyer can ensure truthful category revelation via random assessments carried out with vanishingly small probability, for the rest of this subsection we will ignore these random assessments, we assume that suppliers truthfully report their categories to the buyer, and from here onwards an "assessment" refers to further evaluations on the total cost of ownership given knowledge of the supplier categories.

4. The buyer runs an optimal total-cost procurement auction.

It is worth noting that if the supplier categories are dependent on exogenously observable characteristics (e.g., geographical location, past sustainability failures, etc.) the buyer can readily identify each supplier's category. In this case, Step 2 can be ignored.

After the suppliers disclose their categories, the buyer views the suppliers as ex ante asymmetric, as they are in either category A or B. Then, the above results from Part III, where the buyer faces an ex ante asymmetric supplier base, directly apply.

V. Learning the cost multiplier

In practice, once the buyer collects information from supplier assessments, she needs to translate this information into a cost markup. For example, as we learned from discussions with a third-party supplier sustainability assessment firm, the assessment firm provides the buyer with sustainability ratings for each of their potential suppliers on a scale out of 100. The buyer knows that a rating of 90 is better than a rating of 60, but she may be uncertain exactly how much better (in dollar terms). Consequently, an important question for the buyer is what multiplier she should apply to the supplier ratings when comparing suppliers based on total cost.

Like the issue of needing to do costly supplier assessments to gather data studied in the base model, how the buyer uses supplier assessments in forming total cost comparisons in dollar terms is a very practical challenge in supplier selection. Building off our base model, below we provide (to our knowledge) the first model and analysis to address this. We uncover non-monotonicities with respect to underlying business environment that echo what we saw in §4 (e.g., sensitivity with respect to the outside option cost), and also explain why some sensitivities are different than in §4 (e.g., sensitivity with respect to underlying cost distributions).

Here, we augment our base model to capture the buyer's uncertainty on how precisely to map the assessment results to a cost markup. This mapping should capture the buyer's level of cost sensitivity to the assessed attribute (e.g., buyer's cost sensitivity to supplier sustainability issues) — on which buyer firms may lack information (and which the buyer firms can choose to inform through market research, consumer surveys, internal surveys etc.).

To model this, we assume that the buyer does not know the value of the cost multiplier, however she knows that the cost multiplier Θ is continuously distributed with commonly known cumulative distribution function P (and probability density function ρ) over the finite interval $[\Theta_{(l)}, \Theta_{(u)}]$ with mean μ_Θ (also, multiplier Θ and the cost markup Δ are independent). This multiplier reflects the buyer's underlying cost sensitivity to non-biddable supplier attributes, and can be thought of as a weighting rule which converts the non-biddable attributes into cost markup terms. The buyer has the option to learn about the cost multiplier (through consumer surveys, market research, etc.) prior to the assessment stage after which she will observe the assessment results of all suppliers. Here, in order to focus on the effect of learning the multiplier, we assume that the buyer will assess all suppliers as in our base model. As before, we denote by F and $\tilde{G}$ (with supports $[\Delta_{(l)}, \Delta_{(u)}]$ and $[J_{(l)}, J_{(u)}]$) the cost markup and the virtual production cost distributions, respectively.

If the buyer chooses to learn the cost multiplier Θ, she assigns $\Theta \cdot \delta_i$ as the cost markup to supplier i. If the buyer chooses not to learn the cost multiplier, it can be easily shown that (by appropriately modifying the proof of Lemma 1), the buyer should assign $\mu_\Theta \cdot \delta_i$ as the cost markup to supplier i.

We define the expected value of information on Θ as follows: *EVI* $\triangleq E_{\mathbf{\Delta},\mathbf{J}}[\min\{\mu_\Theta\Delta_1 + J_1, \ldots, \mu_\Theta\Delta_N + J_N, c_0\}] - E_{\mathbf{\Delta},\mathbf{J},\mathbf{\Theta}}[\min\{\Theta\Delta_1 + J_1, \ldots, \Theta\Delta_N + J_N, c_0\}]$. Let us now denote by H the distribution of $\mu_\Theta\Delta + J$, and by H_a the distribution of $\Theta\Delta + J$.

Akin to Proposition 1, Proposition 6 shows that *EVI* is always positive, and establishes the non-monotonicity of *EVI* as the outside option increases.

PROPOSITION 6. *EVI is positive for all distributions F, $\tilde{G}$, and P defined on non-negative intervals. Furthermore, there exists a $x_1, x_2 \in \mathbb{R}^+$ such that EVI increases in c_0 for $c_0 < x_1$, and EVI decreases in c_0 for $x_1 < c_0 < x_2$, and EVI is constant for $c_0 > x_2$. x_1 is precisely where H and H_a cross, and $x_2 = \Theta_{(u)}\Delta_{(u)} + J_{(u)}$.*

Thus far we have seen that the expected value of information on the cost multiplier (*EVI*) behaves very similarly to the expected assessment value (*EAV*). However, below in Proposition 7, we observe that the behavior of *EVI* can significantly differ from *EAV* in a sensitivity analysis. In §4 we saw that, in the absence of the outside option, *EAV* behaves monotonically as we scale up the cost markups. This means that scaling up the cost markups can only make the buyer value the assessments more. However, the same is not true when it comes to learning the cost multiplier. We show below in Proposition 7, among other results, that increasing the magnitude of the cost markups can actually decrease the value of acquiring information about the cost multiplier.

To illustrate this, we consider the case where the buyer does not have an outside option, and for simplicity use normal distributions for Δ and J ($\Delta \sim \text{Normal}(\mu_\Delta, \sigma_\Delta^2)$, and $J \sim \text{Normal}(\mu_J, \sigma_J^2)$). We examine the behavior of the following: $EVI' \triangleq E[(\mu_\Theta \cdot \Delta + J)_{1:N}] - E[(\Theta \cdot \Delta + J)_{1:N}]$.

Proposition 7 first shows that when $\sigma_\Delta = \sigma_J = \sigma$, EVI' is monotone increasing in σ. Hence, EVI' increases with σ_Δ and σ_J when they are exactly comparable in size. Now, consider multiplying Δ by a positive constant γ. Intuitively, one might expect that as γ increases, $\gamma\sigma_\Delta$ increases, and misestimating the buyer's sensitivity to the cost markups (i.e., the size of Θ) becomes potentially very costly for the buyer. Thus, one would expect that as γ increases, the buyer's value of learning the true Θ also increases. However, we find that this is not necessarily the case, and in fact the expected benefit from learning Θ, EVI', is non-monotonic in γ. A similar result holds for the multiplicative constant κ for J. The following proposition formalizes these results.

PROPOSITION 7. *In the absence of an outside option, keeping everything else the same,*

- *Suppose* $\sigma_\Delta = \sigma_J = \sigma$. $\frac{\partial EVI'}{\partial \sigma} > 0$*, hence* EVI' *is increasing in* σ
- *Replace* $\Delta_i, \forall i$ *by* $\gamma \cdot \Delta_i$*, where* $\gamma > 0$. EVI' *is non-monotonic in* γ.
- *Replace* J_i *by* $\kappa \cdot J_i$*, where* $\kappa > 0$. EVI' *is non-monotonic in* κ.

In particular, EVI' *is increasing (decreasing) in* γ *when* $\frac{\sqrt{2}\sigma_J}{\Theta_{(u)}} > \gamma\sigma_\Delta$ ($\frac{\sqrt{2}\sigma_J}{\Theta_{(l)}} < \gamma\sigma_\Delta$)*.* EVI' *is increasing (decreasing) in* κ *when* $\sqrt{2}\Theta_{(l)}\sigma_\Delta > \kappa\sigma_J$ ($\sqrt{2}\Theta_{(u)}\sigma_\Delta < \kappa\sigma_J$)*.*

Proposition 7 shows that EVI' from learning Θ is non-monotonic in $\gamma\sigma_\Delta$. The intuition behind this result is as follows: for small values of $\gamma\sigma_\Delta$ as γ increases, the variability in the cost markups become more important in the buyer's supplier selection decision. Hence, learning Θ becomes increasingly valuable. However, when $\gamma\sigma_\Delta$ becomes large enough to govern the total cost, cost markups become the main driver of the supplier selection decision. It follows that the buyer can now choose a supplier depending on the cost markup realizations, the ranking of which does not change for different values of Θ. Hence, the value of learning Θ decreases.

Similarly, when $\kappa\sigma_J$ is low, learning Θ is not valuable to the buyer since the supplier ranking is largely dependent on the cost markup realizations. However, as κ increases, virtual production cost realizations become increasingly important in the supplier selection decision. Hence, the supplier ranking now depends on the realizations of Θ. Conversely, when $\kappa\sigma_J$ becomes large enough to govern the total cost, the supplier selection decision depends mainly on the virtual production cost realizations, and the value of learning Θ decreases.

Recapping the above, we see that greater variability can diminish the value of information when one cost component – the cost markup or the virtual production cost – tends to "dominate" the other. It is then interesting to ask what happens when neither dominates. In this case, when $\sigma_\Delta = \sigma_J = \sigma$, Proposition 7 shows that *EVI*$'$ monotonically increases in σ.

The managerial takeaway is as follows: when deciding whether to invest in evaluating her cost markup multiplier, the buyer must take a holistic look at the cost drivers and should exert some extra caution. More dispersion can *increase* or *decrease* the benefit of evaluating the cost markup multiplier, depending on how the price and non-price cost drivers compare in size and dispersion.

VI. Imperfect learning

Thus far we have supposed that an assessment on supplier i provides a perfect observation on the cost markup δ_i. However, there may be situations where the assessments do not lead to perfect observations. For completeness, in this subsection we adapt our base model to address this possibility. We will show that our results from §4 carry through.

In order to formally analyze such situations, we introduce a parameter $\alpha \in \mathbb{R}^+$ to represent the level of assessment accuracy, and let ζ_i denote the observation from the assessment on supplier i. In this setting, prior to the assessments (and without ζ_i), the buyer's posterior mean cost markup $E[\Delta|\alpha]$ is a random variable itself.

Given an assessment accuracy level α, we now denote by F_α the distribution of the posterior mean cost markup $E[\Delta|\alpha]$, and by H_a^α the distribution of the adjusted virtual cost with assessments (i.e., $E[\Delta|\alpha]+J$). As before, H denotes the distribution of $\mu_\Delta + J$. For a given assessment accuracy α, the expected value of assessing all N suppliers can similarly be defined as in equation (1):

$$\begin{aligned}
\mathit{EAV}(\alpha) &\triangleq E[\text{TCO without assessments}] - E[\text{TCO with assessments with accuracy } \alpha], \\
&= E[\min\{\mu_\Delta + J_1, \ldots, \mu_\Delta + J_N, c_0\}] \\
&\quad - E[\min\{E[\Delta_1|\alpha] + J_1, \ldots, E[\Delta_M|\alpha] + J_M, E[\Delta_N|\alpha] + J_N, c_0\}].
\end{aligned}$$

The following result extends our previous results from §4.

PROPOSITION 8. *Replace EAV with EAV(α), Δ with $E[\Delta|\alpha]$, and H_a with H_a^α; Lemmas 1-2 and Propositions 1-4 hold as before.*

Intuitively, assessments, even though they are noisy, lead to a spread on the posterior mean of the cost markup, and hence the total-cost distributions, which enables the buyer to differentiate between suppliers.

Further, more accurate assessments should intuitively be more valuable to the buyer (and possibly costlier). To consider such a setting where higher assessment accuracy leads to more precise observations on the cost markup, one can use the following information structure: for $\alpha_2 > \alpha_1$, the distribution of the posterior mean with accuracy α_2 is a mean-preserving spread of the distribution of the posterior mean with accuracy α_1. This holds for example, in Gaussian learning: Let $\Delta_i \sim \text{Normal}(\mu_\Delta, \frac{1}{\beta})$. Suppose that by assessing supplier i, the buyer observes a signal $\zeta_i = \Delta_i + \varepsilon_i$, where $\varepsilon \sim \text{Normal}(0; 1/\alpha)$. Hence, higher levels of α correspond to more accurate and more informative assessments. Having observed ζ_i, the buyer updates her belief on supplier i's cost markup, and forms her posterior mean: $\frac{\beta\mu_\Delta + \alpha\zeta_i}{\alpha+\beta}$. Prior to the assessments, the distribution of the posterior mean, is Normal with mean μ_Δ, and variance $\frac{\alpha}{\beta(\alpha+\beta)}$. Furthermore, the variance increases in the accuracy α. Hence, the distribution of the posterior mean with α_2 is a mean-preserving spread of the distribution of the posterior mean with α_1, for $\alpha_2 > \alpha_1$. With this information structure, higher accuracy leads to a mean-preserving spread on the adjusted virtual cost distribution, and establishes that more accurate assessments are also more valuable for the buyer.

VII. Additional details on *EAVC*

In this extension, we consider mechanisms that proceed as follows. (i) The buyer announces payment and allocation rules; (ii) suppliers report their costs; (iii) the buyer allocates the contract and makes payments per the suppliers' reports; (iv) the buyer experiences the cost markup associated with the winning supplier. Studying such mechanisms parallels our prior analyses. As before, the supplier's private information is limited to c_i, so the buyer faces a one-dimensional mechanism design problem. In the presence of correlation as studied in §4.4, by setting $M = N$ and by replacing $\mathbf{\Delta}$ with $\mathbf{\Delta}|\mathbf{c}$ in the proof of Lemma 1, with this setup it is straightforward to see that in the optimal mechanism without assessments each supplier i truthfully reveals his private information c_i, the buyer assigns supplier i a cost markup $E[\Delta|c_i]$, and the buyer uses the following allocation rule:

$$p_i^*(\mathbf{c}) = \begin{cases} 1 & \text{if } J(c_i) + E[\Delta_i|c_i] \leq J_c(c_j) + E[\Delta_j|c_j], \forall j \neq i \text{ and } J(c_i) + E[\Delta_i|c_i] < c_0, \\ 0 & \text{otherwise.} \end{cases}$$

The buyer pays the winning supplier $t_i^*(\mathbf{c}) = p_i^*(\mathbf{c})c_i + \int_{c_i}^{c_{(u)}} p_i^*(t, \mathbf{c}_{-i})dt$, where $c_{(u)}$ is the upper bound on the production cost c. The buyer's expected total cost from this optimal mechanism is $E_{\mathbf{c}}[\min\{J_c(c_1) + E[\Delta_1|c_1], \ldots, J_c(c_N) + E[\Delta_N|c_N], c_0\}]$.

We denote by $U_i(\hat{c}_i, \mathbf{c}_{-i})$ supplier i's expected payoff when he reveals $\hat{c}_i$ as his production cost. Similar to the proof of Lemma 1, the following incentive compatibility constraint ensures that the suppliers have an incentive to truthfully reveal their production cost: $U_i(c_i, \mathbf{c}_{-i}) = E_{\mathbf{c}_{-i}}[t_i(\mathbf{c}) - p_i(\mathbf{c})c_i] \geq U_i(\hat{c}_i, \mathbf{c}_{-i}),\ \forall i, \hat{c}_i, c_i$. One can verify that $(\mathbf{p}^*, \mathbf{t}^*)$ is incentive compatible if $J_c(c_i) + E[\Delta_i|c_i]$ is increasing in c_i (which ensures that $p_i^*(c_i, \mathbf{c}_{-i})$ is non-increasing in c_i). Hence, we introduce a modified regularity condition that the adjusted virtual cost $E[\Delta|c] + J_c(c)$ is increasing in c.

It is worth noting that as $|\beta|$ increases, the degree of correlation between the production cost c and Δ increases. The correlation coefficient between the correlated variables $c = \epsilon + \beta\Delta$ and Δ is $\rho = \frac{cov(c,\Delta)}{\sigma_c \sigma_\Delta}$, where $cov(c, \Delta)$ is the covariance between c and Δ, and σ_c and σ_Δ are the standard deviations of c and Δ, respectively. Using the bilinearity of covariance, it follows that $\rho = \frac{\beta var(\Delta)}{\sigma_c \sigma_\Delta} = \frac{\beta \sigma_\Delta}{\sigma_c}$, which increases in β for $\beta > 0$, and decreases in β for $\beta < 0$ (note that for $\beta = 0$, correlation coefficient is 0, $E[\Delta|c] = \mu_\Delta$ and the *EAVC* reduces to the *EAV* in our main analysis). Consequently, the degree of correlation increases in $|\beta|$. This means that the buyer can form more precise beliefs on the cost markup having observed c, hence $E[\Delta|c]$ becomes a more precise estimate of Δ as $|\beta|$ increases.

Note that when $c = \epsilon + \beta\Delta$, and when both ϵ and Δ are normally distributed, the pair (c, Δ) defines a bivariate normal distribution as c and Δ are correlated. Further, bivariate normal distributions have the following special property: the distribution for an unobserved variable conditioned on observed values of a subset of variables is also normal. We exploit this property in our numerical experiments when calculating $E[\Delta_i|c_i]$. In particular, conditioning on observing c_i, we have $E[\Delta_i|c_i] = \mu_\Delta + \sigma_\Delta\rho(c_i - \mu_c)/\sigma_c = \mu_\Delta + \beta\frac{\sigma_\Delta^2}{\sigma_c^2}(c_i - \mu_c)$ (see for example, Lindgren et al. (2013), page 267).

Further, for $\beta < 0$, c and Δ are negatively correlated. For the bivariate normal distribution that we use in our numerical experiments, for $\beta < 0$, $\frac{\partial E[\Delta_i|c_i]}{\partial c_i} = \frac{\beta\sigma_\Delta^2}{\sqrt{\sigma_\epsilon^2+\beta^2\sigma_\Delta^2}} < 0$, and $\frac{\partial^2 E[\Delta_i|c_i]}{\partial c_i \partial \beta} = \frac{\sigma_\Delta^2\sigma_\epsilon^2}{\left(\sigma_\Delta^2\beta^2+\sigma_\epsilon^2\right)^{\frac{3}{2}}} > 0$. Hence, $E[\Delta_i|c_i]$ decreases in c_i, and the rate of this decrease increases as $\beta < 0$ decreases. Then, for small enough $\beta < 0$, the regularity condition may be violated, and the incentive compatibility constraint may not hold. In line with this observation, in the numerical experiments in Figure 8, we find that for $\beta \leq -0.075$, $J_c(c) + E[\Delta|c]$ can be decreasing for the parameter space we use in the numerical experiments in in §4.4. Hence, in order to ensure that the incentive compatibility constraint holds, we use $\beta \geq -0.05$ in §4.4.

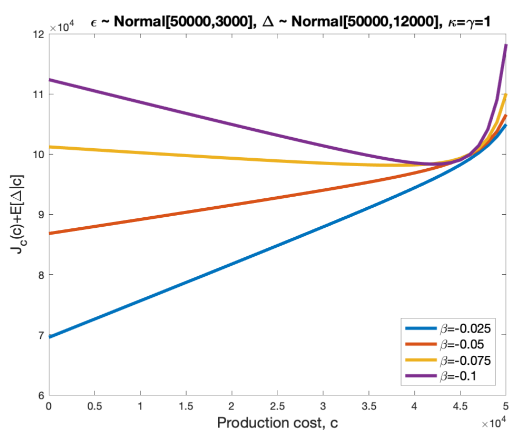

Figure 8 $J_c(c) + E[\Delta|c]$ **can decrease in** c **for** $\beta < 0$**.**

In the absence of an outside option (or facing an outside option that is sufficiently large that for practical purposes it can be ignored), further numerical experiments reported in Figures 9 and 10 suggest that our previous insights on monotonicity in cost and cost markup multipliers as given in Proposition 3 still hold when there is correlation between the production cost and cost markups, and assessments become more (less) valuable as the cost markup (independent production cost component ϵ) dominates the total-cost.

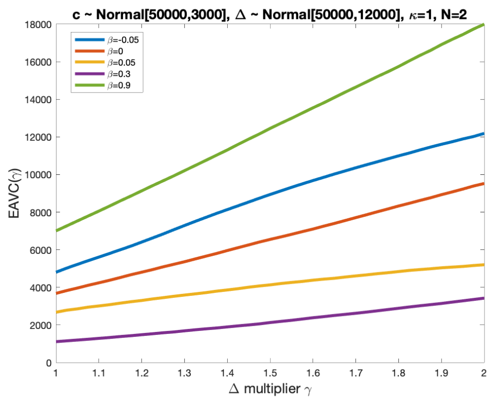

Figure 9 ***EAVC* increases in γ.**

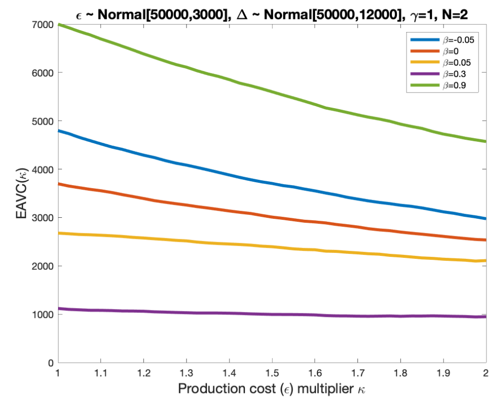

Figure 10 ***EAVC* decreases in κ.**

VIII. Additional details on *EAV* under different auction formats

Echoing our findings in Proposition 3, additional numerical analyses as illustrated below in Figures 11 and 12 suggest that in the absence of an outside option, and for large enough N, as the dispersion of the cost markups increases, *EAV* under all formats increase. Conversely, as the dispersion of the production costs increases, *EAV* under all formats decrease. Note that as one might expect, the *EAV* gap is particularly large (small) for high values of the cost markup (independent production cost component) multiplier.

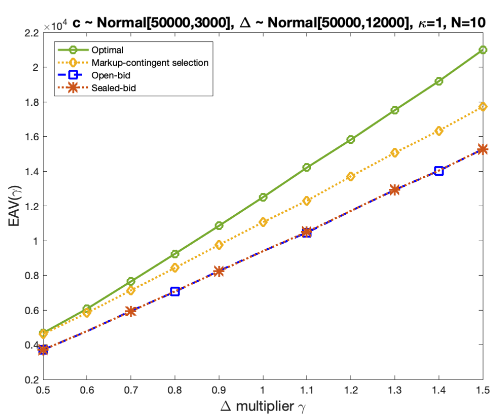

Figure 11 ***EAV* increases in γ.**

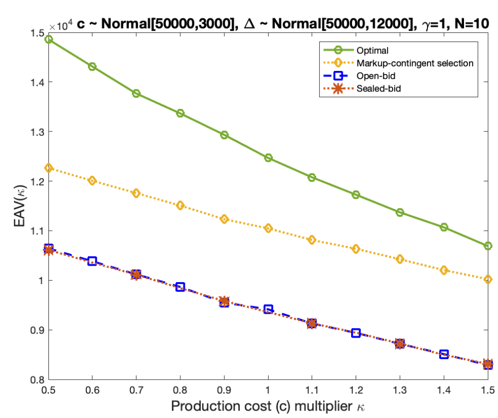

Figure 12 ***EAV* decreases in κ.**

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Online Supplement - Proofs

Proof of Lemma 1 We first derive the optimal mechanism, and then show that this mechanism can be implemented via the auctions referred to in Lemma 1. In searching for the optimal auction mechanism, the revelation principle (Myerson 1981) allows us to focus without loss of optimality on direct mechanisms where each supplier truthfully reveals their private information, namely their production cost. Let p_i denote an assignment rule, and t_i a transfer rule for each i: $p_i(\mathbf{c})$ is the probability that the supplier i wins the auction given production cost vector $\mathbf{c} = (c_1, \ldots, c_N)$; $t_i(\mathbf{c})$ is the payment to supplier i given $\mathbf{c}$. We let $\mathbf{c}_{-i}$ denote the vector of production costs excluding c_i. We denote by c_0 the buyer's cost of non-transaction (outside option); for example, this could correspond to the cost of forgoing the contract, or the cost of in-house production. Using a mechanism design analysis (e.g., Myerson (1981)), the buyer's optimal mechanism (p_i^*, t_i^*) when the buyer has assessments on M, $0 \le M \le N$ suppliers is characterized as follows:

LEMMA 3. *In the optimal mechanism, the buyer assigns each bidder a cost markup as follows: $s_i = \delta_i$ if bidder i was assessed, $s_i = \mu_\Delta$ if bidder i was not assessed. The buyer announces the following allocation and payment rules:*

The buyer allocates the contract to the supplier with the lowest adjusted virtual cost:

$$p_i^*(\mathbf{c}) = \begin{cases} 1 & \text{if } s_i + J(c_i) \le s_j + J(c_j), \forall j \neq i \text{ and } s_i + J(c_i) < c_0, \\ 0 & \text{otherwise.} \end{cases}$$

The buyer pays the winning supplier $t_i^*(\mathbf{c}) = p_i^*(\mathbf{c})c_i + \int_{c_i}^{c(u)} p_i^*(t, \mathbf{c}_{-i})dt$. The buyer's expected total cost from this optimal mechanism is $E_{\mathbf{c}}[\min\{s_1 + J(c_1), \ldots, s_N + J(c_N), c_0\}]$.

Proof of Lemma 3 Without loss of generality, label the suppliers such that $i = \{1, \ldots, M\}$, $0 \le M \le N$, are the assessed suppliers (with known cost markup δ_i), and $i = \{M+1, \ldots, N\}$ are the suppliers who have not been assessed (with unknown cost markup Δ_i). Let us denote by $\mathbf{a}$ the vector of observations that the buyer has on the suppliers' cost markups, i.e., $a_i = \delta_i$ if supplier is assessed, and $a_i = \Delta_i$ if supplier i is not assessed. As per the modeling assumption (and as is done in practice for transparency purposes), the buyer informs an assessed supplier i about a_i, but the supplier i cannot observe $\mathbf{a}_{-i}$ (the set of observations on the other suppliers). Hence, an assessed supplier can observe $a_i = \delta_i$, and the common cost markup distribution F, but the unassesed suppliers can only observe F. Hence, in our problem the buyer (the mechanism designer) has private information that the suppliers cannot observe. One can imagine that the buyer can use this information to manipulate the suppliers' beliefs about each other by the choice of her information disclosure policy on the vector $\mathbf{a}$. Skreta (2011) proves that in an independent private values setting (such as our setting where the total cost of supplier i, $c_i + \delta_i$ is statistically independent from other suppliers' total costs), the informed auctioneer's choice of an information disclosure policy is irreverent in terms of her outcome from the optimal mechanism: i.e, there is no loss of optimality in treating the vector $\mathbf{a}$ as publicly announced (for more details, see Theorem 6 in Skreta (2011)). Hence, below in the optimal mechanism analysis we study the case where the information the buyer collects through the assessments are publicly known by all parties.

Let us denote by $(\mathbf{p}, \mathbf{t})$ a direct revelation mechanism. We denote by $U_i(\hat{c}_i, \mathbf{c}_{-i})$ supplier i's expected payoff when he reveals $\hat{c}_i$ as his production cost. The buyer needs to optimize the following objective function (2), over the set of feasible direct mechanisms satisfying incentive compatibility (3), participation (4), and allocation (5) & (6) constraints.

$$\min_{(\mathbf{p},\mathbf{t})} E_{\mathbf{c},\Delta_{M+1},\ldots,\Delta_N}[\sum_{i=1}^{M}(p_i(\mathbf{c})\delta_i + t_i(\mathbf{c})) + \sum_{i=M+1}^{N}(p_i(\mathbf{c})\Delta_i + t_i(\mathbf{c})) + (1 - \sum_{i=1}^{N} p_i(\mathbf{c}))c_0] \tag{2}$$

subject to:

$$U_i(c_i, \mathbf{c}_{-i}) = E_{\mathbf{c}_{-i}}[t_i(\mathbf{c}) - p_i(\mathbf{c})c_i] \geq U_i(\hat{c}_i, \mathbf{c}_{-i}),\ \forall i, \hat{c}_i, c_i \tag{3}$$

$$U_i(c_i, \mathbf{c}_{-i}) \geq 0,\ \forall i, \tag{4}$$

$$\sum_{i}^{N} p_i(\mathbf{c}) \leq 1, \tag{5}$$

$$p_i(\mathbf{c}) \geq 0,\ \forall i. \tag{6}$$

Using the definition of i's utility function, the expected transfer to supplier i can be written as: $E_{\mathbf{c}_{-i}}[t_i(\mathbf{c})] = U_i(c_i, \mathbf{c}_{-i}) + E_{\mathbf{c_{-i}}}[p_i(\mathbf{c})c_i]$. Then, $E_{\mathbf{c}}[t_i(\mathbf{c})] = \int_{c_{(l)}}^{c_{(u)}} U_i(t, \mathbf{c}_{-i})g(t)dt + E_c[p_i(\mathbf{c})c_i]$, where $g(c_i)$ is the pdf of the production cost.

It follows that we can rewrite (2) as follows: $\min_{(\mathbf{p},\mathbf{t})} E_{\mathbf{c},\Delta_{M+1},\ldots,\Delta_N}[\sum_{i=1}^{M} p_i(\mathbf{c})(\delta_i + c_i) + \sum_{i=M+1}^{N} p_i(\mathbf{c})(\Delta_i + c_i) + \sum_i \int_{c_{(l)}}^{c_{(u)}} U_i(c_i)g(c_i)dc_i + (1-\sum_{i=1}^{N} p_i(\mathbf{c}))c_0]$.

Let us denote $T_i(c_i) \triangleq E_{\mathbf{c}_{-i}}[t_i(\mathbf{c})]$, and $P_i(c_i) \triangleq E_{\mathbf{c}_{-i}}[p_i(\mathbf{c})]$. It follows that $U_i(\mathbf{c}) = T_i(\mathbf{c}) - P_i(\mathbf{c})c_i$. With standard manipulation (see for example Krishna (2010)), it can be shown that for an incentive compatible mechanism $U_i'(\mathbf{c}) = -P_i(\mathbf{c})$.

Now, let us consider $\int_{c_{(l)}}^{c_{(u)}} U_i(c_i)g(c_i)dc_i$. Integrating by parts, for an incentive compatible mechanism we get $\int_{c_{(l)}}^{c_{(u)}} U_i(c_i)g(c_i)dc_i = U_i(c_{(u)}) + E_{\mathbf{c}}[p_i(c_i,\mathbf{c}_{-i})\frac{G(c_i)}{g(c_i)}]$, so the expected cost to the buyer is:

$$W = E_{\mathbf{c},\Delta_{M+1},\ldots,\Delta_N}[\sum_{i=1}^{M} p_i(\mathbf{c})(\delta_i + c_i) + \sum_{i=M+1}^{N} p_i(\mathbf{c})(\Delta_i + c_i) + \sum_{i=1}^{N} U_i(c_{(u)}) + \sum_{i=1}^{N}(p_i(\mathbf{c})\frac{G(c_i)}{g(c_i)}) + (1-\sum_{i=1}^{N} p_i(\mathbf{c}))c_0],$$
$$= E_{\mathbf{c},\Delta_{M+1},\ldots,\Delta_N}[\sum_{i=1}^{M} p_i(\mathbf{c})(\delta_i + J(c_i)) + \sum_{i=M+1}^{N} p_i(\mathbf{c})(\Delta_i + J(c_i)) + (1-\sum_{i=1}^{N} p_i(\mathbf{c}))c_0 + \sum_{i=1}^{N} U_i(c_{(u)})],$$
$$= E_{\mathbf{c}}[\sum_{i=1}^{M} p_i(\mathbf{c})(\delta_i + J(c_i)) + \sum_{i=M+1}^{N} p_i(\mathbf{c})(E[\Delta_i] + J(c_i)) + (1-\sum_{i=1}^{N} p_i(\mathbf{c}))c_0 + \sum_{i=1}^{N} U_i(c_{(u)})].$$

Hence, we can replace the uncertain cost markup term Δ_i with its expectation $E[\Delta_i] = \mu_\Delta$ for the unassessed suppliers $i = \{M+1,\ldots,N\}$. We define a vector $\mathbf{s}$ such that the cost markup $s_i = \delta_i$ if supplier i is assessed, and the cost markup $s_i = \mu_\Delta$ if supplier i is not assessed. Note that W is minimized for $U_i(c_{(u)}) = 0$, and by choosing an assignment rule favoring the supplier i with the lowest $s_i + J(c_i)$ if $s_i + J(c_i) \le c_0$, and awarding the contract to the outside option if $s_i + J(c_i) > c_0$, $\forall i$. This is indeed the optimal assignment rule p_i^* given in the statement of the proposition.

Characterizing the optimal transfer function t_i^* follows from $E_{\mathbf{c}_{-i}}[t_i(\mathbf{c})] = U_i(\mathbf{c}) + E_{\mathbf{c}_{-\mathbf{i}}}[p_i(\mathbf{c})c_i]$ and $U_i(c_{(u)},\mathbf{c}_{-i}) = 0$. When writing the buyer's objective function as W above we assumed that we had an incentive compatible mechanism; one can verify that this indeed is true for $(\mathbf{p}^*,\mathbf{t}^*)$, since $p_i^*(c_i,\mathbf{c}_{-i})$ is non-increasing in c_i.

Let j denote the index of the lowest adjusted virtual cost supplier ($j = \arg\min_i\{s_i + J(c_i)\}$), and let l denote the index of the second-lowest adjusted virtual supplier ($l = \arg\min_{i\neq j}\{s_i + J(c_i)\}$). Now, consider the optimal mechanism given above. Let us denote by $y_i(\boldsymbol{c}_{-i},\boldsymbol{s}) = \sup\{t_i : s_i + J(t_i) \le c_0$ and $s_i + J(t_i) \le s_j + J(c_j), \forall j \neq i\}$ the highest production cost value for supplier i that would still enable him to win under the optimal mechanism. Then, the assignment rule under the optimal mechanism is such that:

$$p_i^*(\boldsymbol{c}) = \begin{cases} 1, & \text{if } c_i \le y_i(\boldsymbol{c}_{-i}, \boldsymbol{s}) \\ 0, & \text{if } c_i > y_i(\boldsymbol{c}_{-i}, \boldsymbol{s}) \end{cases}$$

It follows that

$$\int_{c_i}^{c(u)} p_i^*(t_i, \boldsymbol{c}_{-i}) dt = \begin{cases} y_i(\boldsymbol{c}_{-i}, \boldsymbol{s}) - c_i, & \text{if } c_i \le y_i(\boldsymbol{c}_{-i}, \boldsymbol{s}) \\ 0, & \text{if } c_i > y_i(\boldsymbol{c}_{-i}, \boldsymbol{s}) \end{cases}$$

Then, the transfer function under the optimal mechanism $t_i^*(\boldsymbol{c}) = p_i^*(\boldsymbol{c}) c_i + \int_{c_i}^{c(u)} p_i^*(t, \boldsymbol{c}_{-i}) dt$ can be rewritten as

$$t_i(\boldsymbol{c}) = \begin{cases} y_i(\boldsymbol{c}_{-i}, \boldsymbol{s}), & \text{if } p_i(\boldsymbol{c}) = 1 \\ 0, & \text{if } p_i(\boldsymbol{c}) = 0. \end{cases}$$

Now, consider the transfer to the lowest score supplier (indexed by j) under the optimal mechanism:

$$\begin{aligned} y_j(\boldsymbol{c}_{-j}, \boldsymbol{s}) &= \sup\{t_j : s_j + J(t_j) \le c_0 \text{ and } s_j + J(t_j) \le s_i + J(c_i), \forall i \ne j\}, \\ &= \sup\{t_j : t_j \le J^{-}(c_0 - s_j) \text{ and } t_j \le J^{-1}(s_i + J(c_i) - s_j), \forall i \ne j\}, \\ &= \min\{J^{-1}(c_0 - s_j), \min_{i \ne j}\{J^{-1}(s_i + J(c_i) - s_j)\}\}, \\ &= \min\{J^{-1}(c_0 - s_j), J^{-1}(s_l + J(c_l) - s_j)\}, \text{ where } s_l + J(c_l) \text{ is the second-lowest adjusted virtual cost.} \end{aligned}$$

Hence, in the optimal mechanism, the lowest adjusted virtual cost supplier j is the only supplier who receives a payment, and this ex post payment is equal to $\min\{J^{-1}(c_0 - s_j), J^{-1}(s_l + J(c_l) - s_j)$. Consequently, the expected total cost for the buyer is $E_{\boldsymbol{c}}[\min\{s_1 + J(c_1), \ldots, s_N + J(c_N), c_0\} | \boldsymbol{s}]$. This finalizes the proof on the optimal mechanism as given in Lemma 3.

Then, per Lemma 3, when the buyer does not use assessments on any of the suppliers, $s_i = \mu_\Delta$ for all i, and her expected total cost is $E_{\mathbf{c}}[\min\{\mu_\Delta + J(c)_{1:N}, c_0\}]$. Substituting J as the short hand notation for $J(c)$, we have $E[\text{TCO without assessments}] = E_{\mathbf{J}}[\min\{\mu_\Delta + J_{1:N}, c_0\}]$.

Also, let us denote by $y_i(\boldsymbol{c}_{-i})$ the highest production cost that wins against $\boldsymbol{c}_{-i}$. Then $y_i(\boldsymbol{c}_{-i}) = \max\{z_i : J(z_i) + \mu_\Delta \le c_0 \text{ and } \forall j \ne i, J(z_i) + \mu_\Delta \le J(c_j) + \mu_\Delta\}$. Since we have a symmetric problem, $y_i(\boldsymbol{c}_{-i}) =$

$\min\{J^{-1}(c_0 - \mu_\Delta), \min_{j\neq i} c_j\}$. Hence, the optimal mechanism without assessments can be implemented with a (price-only) open-descending, or sealed-bid auction with a reserve price of $J^{-1}(c_0 - \mu_\Delta)$. This finalizes the proof of Lemma 1.

Proof of Lemma 2 When the buyer assesses all suppliers, $s_i = \delta_i$ for all i, as defined in Lemma 3. Applying Lemma 3, the buyer's expected total cost from the optimal mechanism is $E_{\mathbf{c}}[\min\{\delta_1 + J(c_1), \ldots, \delta_N + J(c_N), c_0\}|\boldsymbol{\delta}]$. Substituting J as the short hand notation for $J(c)$, we have $E[\text{TCO with assessments}|\boldsymbol{\delta}] = E_{\mathbf{J}}[\min\{\delta_1 + J_1, \ldots, \delta_N + J_N, c_0\}|\boldsymbol{\delta}]$.

Proof of Proposition 5. We denote by A and B the supplier categories with lower and higher total base-cost, respectively, i.e., $\Lambda^{(A)} < \Lambda^{(B)}$ where $\Lambda^{(A)} \triangleq c(A) + \Delta(A)$ and $\Lambda^{(B)} \triangleq c(B) + \Delta(B)$.

If the buyer assesses supplier i, she can observe supplier i's cost markup $\Delta(\tau_i) + \epsilon_i^\Delta$. Note that because the suppliers' categories are known by the buyer, suppliers do not earn information rents for this information. However, suppliers still earn information rents from their information on ϵ_i^c. Let J_i (distributed according to distribution $\tilde{G}$) now denote $\epsilon_i^c + \frac{G(\epsilon_i^c)}{g(\epsilon_i^c)}$, the virtual production cost of supplier i.

Facing N_A category-A and N_B category-B suppliers, the buyer's *EAV* if she could assess only M_A category-A, and M_B category-B suppliers is:

$$\begin{aligned}
EAV(M_A, M_B) = E_{\boldsymbol{J}}[&\min\{(\Lambda^{(A)} + J + \mu_{\epsilon^\Delta})_{(1:N_A)}, (\Lambda^{(B)} + J + \mu_{\epsilon^\Delta})_{(1:N_B)}, c_0\}] \\
&- E_{\boldsymbol{J},\boldsymbol{\epsilon}^{\boldsymbol{\Delta}}}[\min\{(\Lambda^{(A)} + J + \epsilon^\Delta)_{(1:M_A)}, (\Lambda^{(A)} + J + \mu_{\epsilon^\Delta})_{(1:N_A - M_A)}, \\
&(\Lambda^{(B)} + J + \epsilon^\Delta)_{(1:M_B)}, (\Lambda^{(B)} + J + \mu_{\epsilon^\Delta})_{(1:N_B - M_B)}, c_0\}].
\end{aligned}$$

We will show that if the buyer is willing to assess one additional supplier, she is better off assessing a category-A supplier. Below we compare the expected procurement costs in two cases: when the additional assessment is on category-B and when the additional assessment is on a category-A supplier:

$$\begin{aligned}
E[\text{TCO with assessments on } M_A, M_B + 1] &= E_{\boldsymbol{J},\boldsymbol{\epsilon}^{\boldsymbol{\Delta}}}[\min\{(\Lambda^{(A)} + J + \epsilon^\Delta)_{(1:M_A)}, (\Lambda^{(A)} + J + \mu_{\epsilon^\Delta})_{(1:N_A - M_A)}, \\
&(\Lambda^{(B)} + J + \epsilon^\Delta)_{(1:M_B+1)}, (\Lambda^{(B)} + J + \mu_{\epsilon^\Delta})_{(1:N_B - M_B - 1)}, c_0\}] \\
&= E_{\boldsymbol{J},\boldsymbol{\epsilon}^{\boldsymbol{\Delta}}}[\min\{(\Lambda^{(A)} + J + \epsilon^\Delta)_{(1:M_A)}, (\Lambda^{(A)} + J + \mu_{\epsilon^\Delta})_{(1:N_A - M_A - 1)},
\end{aligned}$$

$$(\Lambda^{(B)} + J + \epsilon^{\Delta})_{(1:M_B)}, (\Lambda^{(B)} + J + \mu_{\epsilon^\Delta})_{(1:N_B-M_B-1)}, c_0,$$
$$\min\{\Lambda^B - \Lambda^A + J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}, J\} + \mu_{\epsilon^\Delta} + \Lambda^A\}]$$

$$E[\text{TCO with assessments on } M_A+1, M_B] = E_{\boldsymbol{J},\boldsymbol{\epsilon^\Delta}}[\min\{(\Lambda^{(A)} + J + \epsilon^{\Delta})_{(1:M_A+1)}, (\Lambda^{(A)} + J + \mu_{\epsilon^\Delta})_{(1:N_A-M_A-1)},$$
$$(\Lambda^{(B)} + J + \epsilon^{\Delta})_{(1:M_B)}, (\Lambda^{(B)} + J + \mu_{\epsilon^\Delta})_{(1:N_B-M_B)}, c_0\}]$$
$$= E_{\boldsymbol{J},\boldsymbol{\epsilon^\Delta}}[\min\{(\Lambda^{(A)} + J + \epsilon^{\Delta})_{(1:M_A)}, (\Lambda^{(A)} + J + \mu_{\epsilon^\Delta})_{(1:N_A-M_A-1)},$$
$$(\Lambda^{(B)} + J + \epsilon^{\Delta})_{(1:M_B)}, (\Lambda^{(B)} + J + \mu_{\epsilon^\Delta})_{(1:N_B-M_B-1)}, c_0,$$
$$\min\{J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}, \Lambda^B - \Lambda^A + J\} + \mu_{\epsilon^\Delta} + \Lambda^A\}].$$

Note that expressions are equivalent except for $\min\{\Lambda^B - \Lambda^A + J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}, J\}$ and $\min\{J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}, \Lambda^B - \Lambda^A + J\}$ terms. Since $\Lambda^{(A)} < \Lambda^{(B)}$, $\Lambda^B - \Lambda^A + J >_{FOSD} J >_{SOSD} J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}$, $\Lambda^B - \Lambda^A + J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta} >_{FOSD} J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}$, and $J >_{SOSD} J + \epsilon^{\Delta} - \mu_{\epsilon^\Delta}$. Hence, $E[\text{TCO with assessments on } M_A+1, M_B] \leq E[\text{TCO with assessments on } M_A, M_B+1]$. So, given two suppliers in different categories, the buyer prefers to assess whichever has the lowest base-cost. Thus, she would prioritize category-A suppliers in assessments, and would assess a category-B supplier only if all category-A suppliers are assessed.

Let H^A, H^A_a, H^B, and H^B_a denote the cumulative distribution functions of $\Lambda^{(A)} + J + \mu_{\epsilon^\Delta}$, $\Lambda^{(A)} + J + \epsilon^{\Delta}$, $\Lambda^{(B)} + J + \mu_{\epsilon^\Delta}$, and $\Lambda^{(B)} + J + \epsilon^{\Delta}$, respectively.

As in the proof of Proposition 1, we first show that $d^{(1)}_{M_A|M_A<N_A} = \mathit{EAV}(M_A+1, 0) - \mathit{EAV}(M_A, 0)$ is positive. Note that $\mathit{EAV}(M_A, 0) = E[\text{TCO without assessments}] - E[\text{TCO with assessments on } M_A] = \int_0^{c_0}(1 - H^A(x))^{N_A}(1 - H^B(x))^{N_B}dx - \int_0^{c_0}(1 - H^A_a(x))^{M_A}(1 - H^A(x))^{N_A-M_A}(1 - H^B(x))^{N_B}dx$, so $d^{(1)}_{M_A|M_A<N_A} = \int_0^{c_0}(1 - H^B(x))^{N_B}(1 - H^A(x))^{N_A-M_A-1}(1 - H^A_a(x))^{M_A}(H^A_a(x) - H^A(x))dx$.

Note that H^A_a is a mean preserving spread of H^A, and $\int_0^{c_0} H^A_a(x) - H^A(x)dx \geq 0$, $\forall c_0$. Also, note that as per the proof of Proposition 1, there exists $x_1^{(A)}$ such that $H^A_a(x) \geq H^A(x)$ for $x < x_1^{(A)}$, and $H^A_a(x) \leq H^A(x)$ for $x > x_1^{(A)}$. Then, for all $x \leq c_0 < x_1^{(A)}$, $H^A_a(x) - H^A(x)$ is positive, and consequently $d^{(1)}_{M_A|M_A<N_A} = \int_0^{c_0}(1 - H^B(x))^{N_B}(1 - H^A(x))^{N_A-M_A-1}(1 - H^A_a(x))^{M_A}(H^A_a(x) - H^A(x))dx \geq 0$ for $c_0 < x_1^{(A)}$.

Now consider $c_0 > x_1^{(A)}$. Note that $\int_0^{c_0} H_a^A(x) - H^A(x)dx \geq 0$, $\forall c_0$ and $\int_0^{c_0} H_a^A(x) - H^A(x)dx = \int_0^{x_1^{(A)}} H_a^A(x) - H^A(x)dx + \int_{x_1^{(A)}}^{c_0} H_a^A(x) - H^A(x)dx \geq 0$). Also note that $\int_0^{x_1^{(A)}} (H^A(x) - H_a^A(x))dx$ is negative, and $\int_{x_1^{(A)}}^{c_0} (H^A(x) - H_a^A(x))dx$ is positive. Also, note that $(1-H^B(x))^{N_B}(1-H^A(x))^{N_A-M_A-1}(1-H_a^A(x))^{M_A} \geq 0$, and is decreasing in x. Then, $(1-H^B(x))^{N_B}(1-H^A(x))^{N_A-M_A-1}(1-H_a^A(x))^{M_A} \geq (\leq)(1-H^B(x_1^{(A)}))^{N_B}(1-H^A(x_1^{(A)}))^{N_A-M_A-1}(1-H_a^A(x_1^{(A)}))^{M_A}$ for $x \leq (\geq) x_1^{(A)}$. It follows that:

$$
\begin{aligned}
d^{(1)}_{M_A|M_A<N_A} &= \int_0^{c_0} (1-H^B(x))^{N_B}(1-H^A(x))^{N_A-M_A-1}(1-H_a^A(x))^{M_A}(H_a^A(x)-H^A(x))dx \\
&= \int_0^{x_1^{(A)}} (1-H^B(x))^{N_B}(1-H^A(x))^{N_A-M_A-1}(1-H_a^A(x))^{M_A}(H_a^A(x)-H^A(x))dx \\
&+ \int_{x_1^{(A)}}^{c_0} (1-H^B(x))^{N_B}(1-H^A(x))^{N_A-M_A-1}(1-H_a^A(x))^{M_A}(H_a^A(x)-H^A(x))dx \\
&\geq (1-H^B(x_1^{(A)}))^{N_B}(1-H^A(x_1^{(A)}))^{N_A-M_A-1}(1-H_a^A(x_1^{(A)}))^{M_A} \int_0^{x_1^{(A)}} H_a^A(x)-H^A(x)dx \\
&+ (1-H^B(x_1^{(A)}))^{N_B}(1-H^A(x_1^{(A)}))^{N_A-M_A-1}(1-H_a^A(x_1^{(A)}))^{M_A} \int_{x_1^{(A)}}^{c_0} H_a^A(x)-H^A(x)dx \\
&= (1-H^B(x_1^{(A)}))^{N_B}(1-H^A(x_1^{(A)}))^{N_A-M_A-1}(1-H_a^A(x_1^{(A)}))^{M_A} \int_0^{c_0} H_a^A(x)-H^A(x)dx \\
&\geq 0.
\end{aligned}
$$

So, $d^{(1)}_{M_A|M_A<N_A} \geq 0$, and $EAV(M_A, 0)$ is increasing in M_A. Next consider $d^{(2)}_{M_A|M_A<N_A} = d^{(1)}_{M_A+1|M_A+1<N_A} - d^{(1)}_{M_A|M_A<N_A} = -\int_0^{c_0}(1-H^B(x))^{N_B}(1-H^A(x))^{N_A-M_A-2}(1-H_a^A(x))^{M_A}(H_a^A(x) - H^A(x))^2dx$. Since all the terms within the integrand is positive, $d^{(2)}_{M_A|M_A<N_A}$ is negative. It follows that, $EAV(M_A, 0) = E[\text{TCO without assessments}] - E[\text{TCO with assessments on } M_A]$ is concave increasing in M_A.

Now consider $EAV(N_A, M_B)$. We will first show that $d^{(1)}_{M_B|M_B<N_B} \triangleq EAV(N_A, M_B+1) - EAV(N_A, M_B)$ for $M_B < N_B$ is positive. Note that $EAV(N_A, M_B) = E[\text{TCO with assessments on } N_A] - E[\text{TCO with assessments on } N_A \text{ and } M_A] = \int_0^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B}dx - \int_0^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B}(1-H_a^B(x))^{M_B}dx$, so $d^{(1)}_{M_B|M_B<N_B} = \int_0^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B}(H_a^B(x)-H^B(x))dx$.

Note that H_a^B is a mean preserving spread of H^B, and $\int_0^{c_0} H_a^B(x) - H^B(x)dx \geq 0$, $\forall c_0$. Also, note that as per the proof of Proposition 1, there exists $x_1^{(B)}$ such that $H_a^B(x) \geq H^B(x)$ for $x < x_1^{(B)}$, and

$H_a^B(x) \le H^B(x)$ for $x > x_1^{(B)}$. Then, for all $x \le c_0 < x_1^{(B)}$, $H_a^B(x) - H^B(x)$ is positive, and consequently $d^{(1)}_{M_B|M_B<N_B} = \int_0^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B}(H_a^B(x)-H^B(x))dx \ge 0$.

Now consider $c_0 > x_1^{(B)}$. Note that $\int_0^{c_0} H_a^B(x) - H^B(x)dx = \int_0^{x_1^{(B)}} H_a^B(x)-H^B(x)dx + \int_{x_1^{(B)}}^{c_0} H_a^B(x) - H^B(x)dx \ge 0$. Also note that $\int_0^{x_1^{(B)}} H_a^B(x) - H^B(x)dx$ is positive, and $\int_{x_1^{(B)}}^{c_0} H_a^B(x) - H^B(x)dx$ is negative, and that $(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B} \ge 0$, $\forall x$, and is decreasing in x. Then, $(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B} \ge (\le)(1-H_a^A(x_1^{(B)}))^{N_A}(1-H^B(x_1^{(B)}))^{N_B-M_B-1}(1-H_a^B(x_1^{(B)}))^{M_B}$ for $x \le (\ge) x_1^{(B)}$. It follows that:

$$
\begin{aligned}
&\int_0^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B}(H_a^B(x)-H^B(x))dx \\
&= \int_0^{x_1^{(B)}}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B}(H_a^B(x)-H^B(x))dx \\
&+ \int_{x_1^{(B)}}^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-1}(1-H_a^B(x))^{M_B}(H_a^B(x)-H^B(x))dx \\
&\ge (1-H_a^A(x_1^{(B)}))^{N_A}(1-H^B(x_1^{(B)}))^{N_B-M_B-1}(1-H_a^B(x_1^{(B)}))^{M_B}\int_0^{x_1^{(B)}} H_a^B(x)-H^B(x)dx \\
&+ (1-H_a^A(x_1^{(B)}))^{N_A}(1-H^B(x_1^{(B)}))^{N_B-M_B-1}(1-H_a^B(x_1^{(B)}))^{M_B}\int_{x_1^{(B)}}^{c_0} H_a^B(x)-H^B(x)dx \\
&= (1-H_a^A(x_1^{(B)}))^{N_A}(1-H^B(x_1^{(B)}))^{N_B-M_B-1}(1-H_a^B(x_1^{(B)}))^{M_B}\int_0^{c_0} H_a^B(x)-H^B(x)dx \\
&\ge 0.
\end{aligned}
$$

So, $d^{(1)}_{M_B|M_B<N_B} \ge 0$, and *EAV*$(N_A, M_B)$ is increasing in $M_B < N_B$. Next consider $d^{(2)}_{M_B|M_B<N_B} = d^{(1)}_{M_B+1|M_B+1<N_B} - d^{(1)}_{M_B|M_B<N_B} = -\int_0^{c_0}(1-H_a^A(x))^{N_A}(1-H^B(x))^{N_B-M_B-2}(1-H_a^B(x))^{M_B}(H_a^B(x)-H^B(x))^2dx$. Since all the terms within the integrand is positive for all x, $d^{(2)}_{M_B|M_B<N_B}$ is negative. It follows that, *EAV*(N_A, M_B) is concave increasing in M_B. Since the two concave portions of *EAV*(M_A, M_B) have different first and second increments, *EAV* is piecewise-concave and N_A is the vertex point where the two concave portions meet. Consequently, buyer's optimal assessment policy follows the first order conditions as given Proposition 5.

Proof of Proposition 6. With a slight abuse of notation, let us now denote by H the distribution of $\mu_\Theta\Delta + J$, and by H_a the distribution of $\Theta\Delta + J$. Then,

$$EVI = E_{\mathbf{\Delta},\mathbf{J}}[\min\{(\mu_\Theta\Delta+J)_{1:N},c_0\}] - E_{\mathbf{\Delta},\mathbf{J},\mathbf{\Theta}}[\min\{(\Theta\Delta+J)_{1:N},c_0\}] = \int_0^{c_0}(1-H(x))^N dx - \int_0^{c_0}(1-H_a(x))^N dx$$

We note that $\Theta\Delta+J=(\Theta-\mu_\Theta)\Delta+\mu_\Theta\Delta+J$, and $(\Theta-\mu_\Theta)\Delta$ is a zero-mean random variable. Then, the distribution of $\Theta\Delta+J$, i.e., H_a, is a mean-preserving spread of the distribution of $\mu_\Theta\Delta+J$, i.e., H, and $\int_0^t H_a(x)-H(x)dx \geq 0, \forall t\in\mathbb{R}^+$. It follows that the proof of Proposition 1 applies where learning the cost multiplier for the first M suppliers replaces the assessments on M suppliers, and *EVI* replaces *EVA*. It follows that *EVI* is positive.

We now study the effect of changes of c_0 on *EVI*:

$$\frac{\partial EVI}{\partial c_0} = \frac{\partial}{\partial c_0}\int_0^{c_0}(1-H(x))^N dx - \int_0^{c_0}(1-H_a(x))^N dx = (1-H(c_0))^N - (1-H_a(c_0))^N$$

H_a is a mean-preserving spread of H. Hence, there exists a point $x_1\in\mathbb{R}^+$ where $H(x)\leq H_a(x)$ for $x<x_1$, and $H(x)\geq H_a(x)$ for $x>x_1$ (see Proposition 1). Then, $(1-H(c_0))^N-(1-H_a(c_0))^N \geq (\leq) 0$ for $c_0<(>)x_1$. Hence, *EVI* is increasing in c_0 when $c_0<x_1$.

Let us denote $\Theta_{(u)}\Delta_{(u)}+J_{(u)}$ by x_2. Note that for $c_0\geq x_2$ $H(c_0)=H_a(c_0)=1$. Then, for all $c_0\geq x_2$ $\frac{\partial EVI}{\partial c_0}=0$. Hence, *EVI* is constant in c_0 when $c_0\geq x_2$.

Note that for $x_2>c_0>x_1$, $H(c_0)\geq H_a(c_0)$, and $(1-H(c_0))^N-(1-H_a(c_0))^N\leq 0$. Then, $\frac{\partial EVI}{\partial c_0}\leq 0$ for c_0 when $x_1<c_0<x_2$. Hence, *EVI* is decreasing in c_0 when $x_1<c_0<x_2$.

Proof of Proposition 7. First, consider $\sigma_\Delta=\sigma_J=\sigma$. Let us denote by $E[Z_{1:N}]$ the expected first order statistic from a standard normal distribution with N draws. The expected value of information on Θ is:

$$\begin{aligned}
EVI' &= E_{\Delta,J}[(\mu_\Theta\Delta+J)_{1:N}] - E_{\Delta,J,\Theta}[(\Theta\Delta+J)_{1:N}],\\
&= E_{\Delta,J}[(\mu_\Theta\Delta+J)_{1:N}] - \int_{\Theta_{(l)}}^{\Theta_{(u)}} E_{\Delta,J}(\theta\Delta+J)_{1:N}\rho(\theta)d\theta,\\
&= \sqrt{\mu_\Theta^2\sigma_\Delta^2+\sigma_J^2}E[Z_{1:N}]+\mu_\Theta\mu_\Delta+\mu_J - \int_{\Theta_{(l)}}^{\Theta_{(u)}}(\sqrt{\theta^2\sigma_\Delta^2+\sigma_J^2}E[Z_{1:N}]+\theta\mu_\Delta+\mu_J)\rho(\theta)d\theta,\\
&= E[Z_{1:N}]\sigma(\sqrt{\mu_\Theta^2+1} - \int_{\Theta_{(l)}}^{\Theta_{(u)}}\sqrt{\theta^2+1}\rho(\theta)d\theta).
\end{aligned}$$

Hence $\frac{\partial EVI'}{\partial\sigma}=E[Z_{1:N}](\sqrt{\mu_\Theta^2+1}-E[\sqrt{\Theta^2+1}])$. $\sqrt{\Theta^2+1}$ is a convex and strictly increasing function of Θ, so by Jensen's inequality, $\sqrt{\mu_\Theta^2+1}-E[\sqrt{\Theta^2+1}]\leq 0$. Since $E[Z_{1:N}]<0$ for $N\geq 2$, $\frac{\partial EVI'}{\partial\sigma}\geq 0$.

Now, consider $\sigma_\Delta \neq \sigma_J$: $EVI' = E[Z_{1:N}](\sqrt{\mu_\Theta^2\sigma_\Delta^2 + \sigma_J^2} - \int_{\Theta_{(l)}}^{\Theta_{(u)}} \sqrt{\theta^2\sigma_\Delta^2 + \sigma_J^2}\rho(\theta)d\theta)$.

Keeping everything else the same, consider multiplying Δ by a positive multiplier γ. It follows that $EVI'(\gamma) = E[Z_{1:N}](\sqrt{\mu_\Theta^2\gamma^2\sigma_\Delta^2 + \sigma_J^2} - \int_{\Theta_{(l)}}^{\Theta_{(u)}} \sqrt{\theta^2\gamma^2\sigma_\Delta^2 + \sigma_J^2}\rho(\theta)d\theta)$. Then, $\frac{\partial EVI'}{\partial\gamma} = E[Z_{1:N}](\frac{\mu_\Theta^2\gamma\sigma_\Delta^2}{\sqrt{\mu_\Theta^2\gamma^2\sigma_\Delta^2+\sigma_J^2}} - E[\frac{\Theta^2\gamma\sigma_\Delta^2}{\sqrt{\Theta^2\gamma^2\sigma_\Delta^2+\sigma_J^2}}])$. We note that $\frac{\Theta^2\gamma\sigma_\Delta^2}{\sqrt{\Theta^2\gamma^2\sigma_\Delta^2+\sigma_J^2}}$ is a convex (concave) increasing function in Θ when $\frac{\sqrt{2}\sigma_J}{\Theta_{(u)}} > \gamma\sigma_\Delta$ ($\frac{\sqrt{2}\sigma_J}{\Theta_{(l)}} < \gamma\sigma_\Delta$). Then, by Jensen's inequality, $\frac{\mu_\Theta^2\gamma\sigma_\Delta^2}{\sqrt{\mu_\Theta^2\gamma^2\sigma_\Delta^2+\sigma_J^2}} - E[\frac{\Theta^2\gamma\sigma_\Delta^2}{\sqrt{\Theta^2\gamma^2\sigma_\Delta^2+\sigma_J^2}}] \leq (\geq) 0$, hence $\frac{\partial EVI'}{\partial\gamma} \geq (\leq) 0$ when $\frac{\sqrt{2}\sigma_J}{\Theta_{(u)}} > \gamma\sigma_\Delta$ ($\frac{\sqrt{2}\sigma_J}{\Theta_{(l)}} < \gamma\sigma_\Delta$).

Now, keeping everything else the same in the original *EVI'* expression, consider multiplying J by a positive multiplier κ. It follows that $EVI'(\kappa) = E[Z_{1:N}](\sqrt{\mu_\Theta^2\sigma_\Delta^2 + \kappa^2\sigma_J^2} - \int_{\Theta_{(l)}}^{\Theta_{(u)}} \sqrt{\theta^2\sigma_\Delta^2 + \kappa^2\sigma_J^2}\rho(\theta)d\theta)$. Then, $\frac{\partial EVI'}{\partial\kappa} = E[Z_{1:N}](\frac{\kappa\sigma_J^2}{\sqrt{\mu_\Theta^2\sigma_\Delta^2+\kappa^2\sigma_J^2}} - E[\frac{\kappa\sigma_J^2}{\sqrt{\Theta^2\sigma_\Delta^2+\kappa^2\sigma_J^2}}])$. We note that $\frac{\kappa\sigma_J^2}{\sqrt{\Theta^2\sigma_\Delta^2+\kappa^2\sigma_J^2}}$ is a convex (concave) decreasing function in Θ when $\sqrt{2}\Theta_{(l)}\sigma_\Delta > \kappa\sigma_J$ ($\sqrt{2}\Theta_{(u)}\sigma_\Delta < \kappa\sigma_J$). Then, by Jensen's inequality, $\frac{\kappa\sigma_J^2}{\sqrt{\mu_\Theta^2\sigma_\Delta^2+\sigma_J^2}} - E[\frac{\kappa\sigma_J^2}{\sqrt{\Theta^2\sigma_\Delta^2+\sigma_J^2}}] \leq (\geq) 0$, hence $\frac{\partial EVI'}{\partial\kappa} \geq (\leq) 0$ when $\sqrt{2}\Theta_{(l)}\sigma_\Delta > \kappa\sigma_J$ ($\sqrt{2}\Theta_{(u)}\sigma_\Delta < \kappa\sigma_J$).

Proof of Proposition 8. Note that prior to assessments, the posterior mean of supplier i's cost markup $E[\Delta|\alpha]$ is a random variable with mean μ_Δ. Then, $H_a^\alpha(x)$ (the cdf of $E[\Delta|\alpha] + J$) is a mean-preserving spread of H (the cdf of $\mu_\Delta + J$). Now consider $EAV(\alpha)$:

$$
\begin{aligned}
EAV(\alpha) &\triangleq E[\text{TCO without assessments}] - E[\text{TCO with assessments with accuracy } \alpha],\\
&= E[\min\{\mu_\Delta + J_1, \ldots, \mu_\Delta + J_N, c_0\}]\\
&- E[\min\{E[\Delta_1|\alpha] + J_1, \ldots, E[\Delta_M|\alpha] + J_M, E[\Delta_N|\alpha] + J_N, c_0\}],\\
&= \int_0^{c_0} (1 - H(x))^N - (1 - H_a^\alpha(x))^N dx.
\end{aligned}
$$

Note that the structure of $EAV(\alpha)$ is identical to *EAV* given in (1) in §3. Further, Lemmas 1-2 and Propositions 1-4 hold for any generic H and H_a, where H_a is a mean-preserving spread of H. Hence, by substituting $E[\Delta|\alpha]$ for Δ, H_a^α for H_a, the proofs of Lemmas 1-2 and Propositions 1-4 directly apply.