

Online Appendix for “Tractability and Detail-Neutrality in Incentive Contracting”

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November 12, 2008

D Incentive Compatibility of Contract when Timing is Reversed

In the core model, noise η_t precedes the action a_t in each period. This section shows that, if the timing is reversed, the optimal contract in Theorem 1 still induces the target path of actions, although we can no longer prove that it is incentive compatible. For brevity, we consider $T = 1$.

The agent chooses

$$a^* \in \arg \max_a \mathbb{E} [u(v(c(a + \eta)) - g(a))],$$

where η is now unknown. With the proposed contract $v(c(r)) = g'(a^*)r + K$, so the maximization problem is:

$$a^* \in \arg \max_a \mathbb{E} [u(g'(a^*)a - g(a) + g'(a^*)\eta)]$$

This is maximized pointwise by maximizing $g'(a^*)a - g(a)$ over a , i.e. for $a = a^*$.

However, we can no longer prove that the contract in Theorem 1 is optimal. In general, results from Holmstrom (1979) indicate that it is not optimal with that “reversed” timing.

E Multidimensional Signal and Action

While the core model involves a single signal and action, this section shows that our contract is robust to a setting of multidimensional signals and actions. For brevity, we only analyze the discrete-time one-period case, since the continuous time extension is similar. The agent now takes a multidimensional action $\mathbf{a} \in \mathcal{A}$, which is a compact subset of \mathbb{R}^I for some integer I . (Note that in this section, bold font has a different usage than in the proof of Theorem 1.) The signal is also multidimensional:

$$\mathbf{r} = \mathbf{b}(\mathbf{a}) + \boldsymbol{\eta},$$

where $\boldsymbol{\eta}, \mathbf{r} \in \mathbb{R}^S$, and $\mathbf{b}: \mathcal{A} \in \mathbb{R}^I \rightarrow \mathbb{R}^S$. The signal and action can be of different dimensions. In the core model, $S = I = 1$ and $\mathbf{b}(a) = a$. As before, the contract is $c(\mathbf{r})$ and the indirect felicity function is $V(\mathbf{r}) = v(c(\mathbf{r}))$. The following Proposition states the optimal contract.

Proposition 3 (*Optimal contract, discrete time, multidimensional signal and action*). Define the $I \times S$ matrix $L = \mathbf{b}'(\mathbf{a}^*)^\top$ i.e. explicitly $L_{ij} = \frac{\partial \mathbf{b}_j}{\partial a_i}(a_1^*, \dots, a_I^*)$, and assume that there is a vector $\theta \in \mathbb{R}^S$ such that

$$L\theta = g'(\mathbf{a}^*), \quad (60)$$

i.e., explicitly:

$$\forall i = 1 \dots I, \sum_{j=1}^S \frac{\partial \mathbf{b}_j}{\partial a_i}(a_1^*, \dots, a_I^*) \theta_j = \frac{\partial g}{\partial a_i}(a_1^*, \dots, a_I^*).$$

The optimal contract is given by:

$$c(\mathbf{r}) = v^{-1}(\theta \mathbf{r} + K(\mathbf{r})), \quad (61)$$

i.e., explicitly, $c(\mathbf{r}) = v^{-1}\left(\sum_{j=1}^S \theta_j r_j + K(r_1, \dots, r_n)\right)$, where the function $K(\cdot)$ is the solution of the following optimization problem:

$$\min_{K(\cdot)} \mathbb{E}[K(\mathbf{b}(\mathbf{a}^*) + \boldsymbol{\eta})] \text{ subject to}$$

$$\forall \mathbf{r}, LK'(\mathbf{r}) = 0 \quad (62)$$

$$\mathbb{E}[u(\theta(\mathbf{b}(\mathbf{a}^*) + \boldsymbol{\eta}) + K(\mathbf{b}(\mathbf{a}^*) + \boldsymbol{\eta}) - g(\mathbf{a}^*))] \geq \underline{u}.$$

Proof. Here we derive the first-order condition; the remainder of the proof is as in Theorem 1 of the main paper. Incentive compatibility requires that, for all $\boldsymbol{\eta}$

$$\mathbf{a}^* \in \arg \max_{\mathbf{a}} V(\mathbf{b}(\mathbf{a}) + \boldsymbol{\eta}) - g(\mathbf{a}),$$

and so:

$$V'(\mathbf{b}(\mathbf{a}^*) + \boldsymbol{\eta}) \mathbf{b}'(\mathbf{a}^*) - g'(\mathbf{a}^*) = 0, \quad (63)$$

where V' is a S -dimensional vector, $\mathbf{b}'(\mathbf{a}^*)$ is a $S \times I$ matrix, and $g'(\mathbf{a}^*)$ is a I -dimensional vector. Integrating equation (63) gives: $V(\mathbf{r}) = \theta \mathbf{r} + K(\mathbf{r})$, where $\theta \mathbf{r} = \sum_{i=1}^S \theta_i r_i$, and $LK'(\mathbf{r}) = 0$.

Note that $K(\mathbf{r})$ is now a function and so determined by solving an optimization problem. Previously, K was a constant and determined by solving an equality. ■

We now analyze two specific applications of this extension.

Two signals. The agent takes a single action, but there are two signals of performance:

$$r_1 = a + \varepsilon_1, \quad r_2 = a + \varepsilon_2.$$

In this case, $L = (1 \ 1)$. Therefore, with $\theta = (\theta_1, \theta_2) \in \mathbb{R}^2$, (60) becomes: $\theta_1 + \theta_2 = g'(a^*)$. For example, we can take $\theta_1 = \theta_2 = g'(a^*)/2$. Next, (62) becomes: $\partial K/\partial r_1 + \partial K/\partial r_2 = 0$. It is well known that this can be integrated into: $K(r_1, r_2) = k(r_1 - r_2)$ for a function k . Hence, the optimal contract can be written:

$$c = v^{-1} \left(g'(a^*) \left(\frac{r_1 + r_2}{2} \right) + k(r_1 - r_2) \right),$$

where the function $k(\cdot)$ is chosen to minimize the cost of the contract subject to the participation constraint. As in Holmstrom (1979), all informative signals should be used to determine the agent's compensation.

Relative performance evaluation. Again, there is a single action and two signals, but the second signal is independent of the agent's action, as in Holmstrom (1982):

$$r_1 = a + \varepsilon_1, \quad r_2 = \varepsilon_2$$

In this case, $L = (1 \ 0)$. Therefore, with $\theta = (\theta_1, \theta_2) \in \mathbb{R}^2$, (60) becomes: $\theta_1 = g'(a^*)$. Next, (62) becomes: $\partial K/\partial r_1 = 0$, so that $K(r_1, r_2) = k(r_2)$ for a function k . Hence, the optimal contract can be written:

$$c = v^{-1} (g'(a^*) r_1 + k(r_2)).$$

The second signal enters the contract even though it is unaffected by the agent's action, since it may be correlated with the noise in the first signal.

F Proofs of Mathematical Lemmas

This section contains proofs of some of the mathematical lemmas featured in the appendices of the main paper.

Proof of Lemma 4 We thank Chris Evans for suggesting the proof strategy for this Lemma. We assume $a < b$.

We first prove the Lemma when $j(x) = 0 \forall x$. For a positive integer n , define $k_n = (b - a) / n$, and the function $r_n(x)$ as

$$r_n(x) = \begin{cases} \frac{f(x) - f(x - k_n)}{k_n} & \text{for } x \in [a + k_n, b] \\ 0 & \text{for } x \in [a, a + k_n]. \end{cases}$$

We have for $x \in (a, b]$, $\liminf_{n \rightarrow \infty} r_n(x) \geq \liminf_{\varepsilon \downarrow 0} \frac{f(x) - f(x - \varepsilon)}{\varepsilon} \geq 0$.

Define $I_n = \int_a^b r_n(x) dx$. As $f + h$ is nondecreasing and k is C^1 , $\frac{f(x) - f(x - k_n)}{k_n} \geq \frac{-h(x) + h(x - k_n)}{k_n} \geq -\sup_{[a, b]} h'(x)$. Therefore, $r_n(x) \geq \min(0, -\sup_{[a, b]} h'(x)) \forall x$. Hence we can apply Fatou's lemma, which shows:

$$\liminf_{n \rightarrow \infty} I_n = \liminf_{n \rightarrow \infty} \int_a^b r_n(x) dx \geq \int_a^b \liminf_{n \rightarrow \infty} r_n(x) dx \geq 0.$$

Next, observe that $I_n = \int_{a+k_n}^b \frac{f(x) - f(x - k_n)}{k_n} dx$ consists of telescoping sums, so:

$$\begin{aligned} I_n &= \int_{b-k_n}^b \frac{f(x)}{k_n} dx - \int_a^{a+k_n} \frac{f(x)}{k_n} dx \\ &= f(b) - f(a) - \int_{b-k_n}^b \frac{f(b) - f(x)}{k_n} dx - \int_a^{a+k_n} \frac{f(x) - f(a)}{k_n} dx = f(b) - f(a) - B_n - A_n. \end{aligned}$$

We first minorize A_n . From condition (ii) of the Lemma, for any $\varepsilon > 0$, there is an $\eta > 0$, such that for $x \in [a, a + \eta]$, $f(x) - f(a) \geq -\varepsilon$. For n large enough such that $k_n \leq \eta$,

$$A_n = \int_a^{a+k_n} \frac{f(x) - f(a)}{k_n} dx \geq \int_a^{a+k_n} \frac{-\varepsilon}{k_n} dx = -\varepsilon,$$

and so $\liminf_{n \rightarrow \infty} A_n \geq 0$.

We next minorize B_n . Since $f'_-(b) \geq 0$ for every $\varepsilon > 0$, there exists a $\delta > 0$ s.t. for $x \in [b - \delta, b]$, $(f(b) - f(x)) / (b - x) \geq -\varepsilon$. Therefore, for n sufficiently large so that $k_n \leq \delta$,

$$B_n = \int_{b-k_n}^b \frac{f(b) - f(x)}{k_n} dx \geq \int_{b-k_n}^b \frac{(-\varepsilon)(b - x)}{k_n} dx = -\varepsilon \frac{k_n}{2},$$

and so $\liminf_{n \rightarrow \infty} B_n \geq 0$.

Finally, since $f(b) - f(a) = I_n + A_n + B_n$, we have

$$f(b) - f(a) = \liminf_{n \rightarrow \infty} (I_n + A_n + B_n) \geq \liminf_{n \rightarrow \infty} I_n + \liminf_{n \rightarrow \infty} A_n + \liminf_{n \rightarrow \infty} B_n \geq 0.$$

We now prove the general case. Define $F(x) = f(x) - \int_a^x j(t) dt$. Then, $F'_-(x) \geq 0$. By the above result, $F(b) - F(a) \geq 0$.

Proof of Lemma 5

Let $(y_n) \uparrow x$ be a sequence such that

$$f'_-(x) = \lim_{y_n \uparrow x} \frac{f(x) - f(y_n)}{x - y_n}.$$

We can further assume that $\lim_{n \rightarrow \infty} f(y_n)$ exists (if not, then we can choose a subsequence y_{n_k} such that $\lim_{n_k \rightarrow \infty} f(y_{n_k})$ exists and replace y_n by y_{n_k}).

If $\lim_{n \rightarrow \infty} f(y_n) = f(x)$, Then,

$$\begin{aligned} (h \circ f)'_-(x) &= \liminf_{y \uparrow x} \frac{h \circ f(x) - h \circ f(y)}{x - y} \\ &\leq \lim_{y_n \uparrow x} \frac{h \circ f(x) - h \circ f(y_n)}{x - y_n} \\ &= \lim_{y_n \uparrow x} \frac{h \circ f(x) - h \circ f(y_n)}{f(x) - f(y_n)} \frac{f(x) - f(y_n)}{x - y_n} \\ &= h'(f(x)) f'_-(x). \end{aligned}$$

If $\lim_{n \rightarrow \infty} f(y_n) < f(x)$, then $f'_-(x) = \infty$, since $h'(f(x)) > 0$, we still have $(h \circ f)'_-(x) \leq h'(f(x)) f'_-(x)$.

If $\lim_{n \rightarrow \infty} f(y_n) > f(x)$, then $(h \circ f)'_-(x) \leq \lim_{y_n \uparrow x} \frac{h \circ f(x) - h \circ f(y_n)}{x - y_n} = -\infty$, hence $(h \circ f)'_-(x) \leq h'(f(x)) f'_-(x)$.

On the other hand, suppose $(\hat{y}_n) \uparrow x$ be a sequence such that

$$(h \circ f)'_-(x) = \lim_{\hat{y}_n \uparrow x} \frac{h \circ f(x) - h \circ f(\hat{y}_n)}{x - \hat{y}_n},$$

and that $\lim_{n \rightarrow \infty} f(\hat{y}_n)$ exists. If $\lim_{n \rightarrow \infty} f(\hat{y}_n) = f(x)$, Then,

$$\begin{aligned} (h \circ f)'_-(x) &= \lim_{\hat{y}_n \uparrow x} \frac{h \circ f(x) - h \circ f(\hat{y}_n)}{x - \hat{y}_n} \\ &= \lim_{\hat{y}_n \uparrow x} \frac{h \circ f(x) - h \circ f(\hat{y}_n)}{f(x) - f(\hat{y}_n)} \frac{f(x) - f(\hat{y}_n)}{x - \hat{y}_n} \\ &= \lim_{\hat{y}_n \uparrow x} \frac{h \circ f(x) - h \circ f(\hat{y}_n)}{f(x) - f(\hat{y}_n)} \lim_{\hat{y}_n \uparrow x} \frac{f(x) - f(\hat{y}_n)}{x - \hat{y}_n} \\ &= h'(f(x)) \lim_{\hat{y}_n \uparrow x} \frac{f(x) - f(\hat{y}_n)}{x - \hat{y}_n} \\ &\geq h'(f(x)) f'_-(x). \end{aligned}$$

Note that the existence of $\lim_{\hat{y}_n \uparrow x} \frac{h \circ f(x) - h \circ f(\hat{y}_n)}{x - \hat{y}_n}$ and $\lim_{\hat{y}_n \uparrow x} \frac{h \circ f(x) - h \circ f(\hat{y}_n)}{f(x) - f(\hat{y}_n)}$ guarantees the existence of $\lim_{\hat{y}_n \uparrow x} \frac{f(x) - f(\hat{y}_n)}{x - \hat{y}_n}$.

If $\lim_{n \rightarrow \infty} f(\hat{y}_n) < f(x)$, then $(h \circ f)'_-(x) = \infty \geq h'(f(x)) f'_-(x)$.

If $\lim_{n \rightarrow \infty} f(\hat{y}_n) > f(x)$, then $f'_-(x) \leq \lim_{\hat{y}_n \uparrow x} \frac{f(x) - f(\hat{y}_n)}{x - \hat{y}_n} = -\infty \leq (h \circ f)'_-(x)$. Therefore, $(h \circ f)'_-(x) = h'(f(x)) f'_-(x)$.

Proof of Lemma 6

We use

$$\begin{aligned} (f + h)'_-(x) &= \liminf_{y \uparrow x} \frac{f(x) + h(x) - f(y) - h(y)}{x - y} = \liminf_{y \uparrow x} \left(\frac{f(x) - f(y)}{x - y} + \frac{h(x) - h(y)}{x - y} \right) \\ &\geq \liminf_{y \uparrow x} \frac{f(x) - f(y)}{x - y} + \liminf_{y \uparrow x} \frac{h(x) - h(y)}{x - y} = f'_-(x) + h'_-(x). \end{aligned}$$

When h is differentiable at x ,

$$(f + h)'_-(x) = \liminf_{y \uparrow x} \frac{f(x) - f(y)}{x - y} + \lim_{y \uparrow x} \frac{h(x) - h(y)}{x - y} = f'_-(x) + h'(x).$$

Proof of Lemma 7

We wish to prove that $\mathbb{E}[h(X)] \geq \mathbb{E}[h(Y)]$ for any concave function h . Define $I(\delta) = \mathbb{E}[h(X + \delta(Y - X))]$ for $\delta \in [0, 1]$, so that

$$\begin{aligned} I''(\delta) &= \mathbb{E}[h''(X + \delta(Y - X))(Y - X)^2] \leq 0 \\ I'(0) &= \mathbb{E}[h'(X)(Y - X)] = \mathbb{E}\left[h'(X) \left(\int_0^T \gamma_t dZ_t \right)\right], \end{aligned}$$

where $\gamma_t = \beta_t - \alpha_t$, and $\gamma_t \geq 0$ almost surely. We wish to prove $I(1) \leq I(0)$. Since I is concave, it is sufficient to prove that $I'(0) \leq 0$.

We next use some basic results from Malliavin calculus (see, e.g., Di Nunno, Oksendal and Proske (2008)). The integration by parts formula for Malliavin calculus yields:

$$I'(0) = \mathbb{E}\left[h'(X) \left(\int_0^T \gamma_t dZ_t \right)\right] = \mathbb{E}\left[\int_0^T (D_t h'(X)) \gamma_t dt \right],$$

where $D_t h'(X)$ is the Malliavin derivative of $h'(X)$ at time t . Since $(\alpha_s)_{s \in [0, T]}$ is deterministic. Therefore, the calculation of $D_t h'(X)$ is straightforward:

$$D_t h'(X) \equiv D_t h' \left(\int_0^T \alpha_s dZ_s \right) = h'' \left(\int_0^T \alpha_s dZ_s \right) \alpha_t = h''(X) \alpha_t.$$

Hence, we have:

$$I'(0) = \mathbb{E} \left[\int_0^T (D_t h'(X)) \gamma_t dt \right] = \mathbb{E} \left[\int_0^T h''(X) \alpha_t \gamma_t dt \right].$$

Since $h''(X) \leq 0$ (because h is concave), and α_t and γ_t are nonnegative, we have $h''(X) \alpha_t \gamma_t \leq 0$. Therefore, $I'(0) \leq 0$ as required.

Proof of Lemma 8

We commence the proof with a Lemma.

Lemma 9 Consider a differentiable function f , two continuously differentiable random variables X and Y (not necessarily independent), two constants a and b such that $\mathbb{E}[f(X+a)] = \mathbb{E}[f(Y+b)]$, and an interval I such that (i) $f'(x) > 0 \forall x \in I$ and (ii) almost surely, $X+a$ and $Y+b$ are in I . Then,

$$|a-b| \leq \frac{\sup_I f'}{\inf_I f'} \mathbb{E}[|X-Y|]. \quad (64)$$

The Lemma implies that when X and Y are “close”, then a and b are also close.

Proof. By redefining if necessary $Y' = Y + b$, $X' = X + b$, it is sufficient to consider the case $b = 0$. Define $H = X - Y + a$. From the Intermediate Value Theorem, for any Y, H , there is a value $\theta(Y, H)$ such that $f(Y+H) - f(Y) = f'(Y + \theta(Y, H)H)H$. In addition, $Y + \theta(Y, H)H \in I$ almost surely. Hence,

$$\begin{aligned} 0 &= \mathbb{E}[f(Y)] - \mathbb{E}[f(X+a)] = \mathbb{E}[f(Y)] - \mathbb{E}[f(Y+H)] = \mathbb{E}[f'(Y + \theta(Y, H)H)(X - Y + a)] \\ &= \mathbb{E}[f'(Y + \theta(Y, H)H)(X - Y)] + a \mathbb{E}[f'(Y + \theta(Y, H)H)]. \end{aligned}$$

Thus,

$$|a| = \frac{|\mathbb{E}[f'(Y + \theta(Y, H)H)(X - Y)]|}{\mathbb{E}[f'(Y + \theta(Y, H)H)]} \leq \frac{(\sup_I f') \mathbb{E}[|X - Y|]}{\inf_I f'}.$$

■

We now turn to the main proof. Consider contract A that implements action $A(\eta)$, and contract B that implements $B(\eta)$. Define

$$X = \int_{\underline{\eta}}^{\eta} g'(A(x)) dx, \quad Y = \int_{\underline{\eta}}^{\eta} g'(B(x)) dx,$$

and k, k' such that

$$\underline{u} = \mathbb{E}[u(X+k)] = \mathbb{E}[u(Y+k')]. \quad (65)$$

From Proposition 3, the felicity of contract A is $X + k + g(A(\eta))$, and the felicity of contract B is $Y + k' + g(B(\eta))$.

We prove the Lemma by demonstrating a sequence of three inequalities.

1). *Inequality regarding $|k - k'|$.* Since $0 \leq X \leq (\bar{\eta} - \underline{\eta}) g'(\bar{a})$, we have

$$\begin{aligned} u(k) &\leq \underline{u} = \mathbb{E}[u(X + k)] \leq u(k + (\bar{\eta} - \underline{\eta}) g'(\bar{a})) \\ &\Rightarrow u^{-1}(\underline{u}) - (\bar{\eta} - \underline{\eta}) g'(\bar{a}) \leq k \leq u^{-1}(\underline{u}). \end{aligned}$$

We therefore have $\alpha \leq k + X \leq \beta$, where

$$\alpha \equiv u^{-1}(\underline{u}) - (\bar{\eta} - \underline{\eta}) g'(\bar{a}) \quad \text{and} \quad \beta \equiv u^{-1}(\underline{u}) + (\bar{\eta} - \underline{\eta}) g'(\bar{a}). \quad (66)$$

By the same reasoning, $\alpha \leq k' + Y \leq \beta$.

Applying Lemma 9 to equation (65), function u and interval $[\alpha, \beta]$, we obtain: $|k - k'| \leq \frac{\sup_{[\alpha, \beta]} u'}{\inf_{[\alpha, \beta]} u'} \mathbb{E}|X - Y|$. Since u is concave, this yields the inequality:

$$|k - k'| \leq \frac{u'(\alpha)}{u'(\beta)} \mathbb{E}|X - Y|. \quad (67)$$

2). *Inequality regarding $\mathbb{E}|X - Y|$.* We have:

$$\begin{aligned} \mathbb{E}|X - Y| &= \mathbb{E} \left| \int_{\underline{\eta}}^{\tilde{\eta}} (g'(A(x)) - g'(B(x))) dx \right| \\ &\leq (\sup g'') \mathbb{E} \left[\int_{\underline{\eta}}^{\tilde{\eta}} |A(x) - B(x)| dx \right] = (\sup g'') \mathbb{E} \left[\int_{\underline{\eta}}^{\tilde{\eta}} |A(x) - B(x)| 1_{x \leq \tilde{\eta}} dx \right] \\ &= (\sup g'') \int_{\underline{\eta}}^{\tilde{\eta}} |A(x) - B(x)| \mathbb{E}[1_{x \leq \tilde{\eta}}] dx \\ &= (\sup g'') \int_{\underline{\eta}}^{\tilde{\eta}} |A(x) - B(x)| \bar{F}(x) dx, \text{ defining } \bar{F}(x) = P(\eta \geq x) \\ &= (\sup g'') \int_{\underline{\eta}}^{\tilde{\eta}} |A(x) - B(x)| \frac{\bar{F}(x)}{f(x)} f(x) dx \\ &\leq (\sup g'') \left(\sup \frac{\bar{F}}{f} \right) \int_{\underline{\eta}}^{\tilde{\eta}} |A(x) - B(x)| f(x) dx = (\sup g'') \left(\sup \frac{\bar{F}}{f} \right) \mathbb{E}|A(\tilde{\eta}) - B(\tilde{\eta})|, \end{aligned}$$

yielding the inequality

$$\mathbb{E}|X - Y| \leq (\sup g'') \left(\sup \frac{\bar{F}}{f} \right) \mathbb{E}|A(\tilde{\eta}) - B(\tilde{\eta})|. \quad (68)$$

3). *Inequality regarding the difference in costs.* We can now compare the costs of the two contracts, which we denote \mathcal{C}_A and \mathcal{C}_B . We find:

$$\begin{aligned}
|\mathcal{C}_A - \mathcal{C}_B| &= |\mathbf{E} [v^{-1}(X + k + g(A(\eta))) - v^{-1}(Y + k + g(B(\eta)))]| \\
&\leq \left(\sup_{[\alpha + \inf g, \beta + \sup g]} (v^{-1})' \right) \cdot \mathbf{E} [|X + k + g(A(\eta)) - (Y + k + g(B(\eta)))|] \\
&\leq D (\mathbf{E} |X - Y| + |k - k'| + \mathbf{E} [g(A(\eta)) - g(B(\eta))]) , \text{ defining } D = (v^{-1})' (\beta + g(\bar{a})) \\
&\leq D \left(1 + \frac{u'(\alpha)}{u'(\beta)} \right) \mathbf{E} |X - Y| + D g'(\bar{a}) \mathbf{E} |A(\eta) - B(\eta)| , \text{ by equation (67)}
\end{aligned}$$

Define

$$\Lambda = \left[\left(1 + \frac{u'(\alpha)}{u'(\beta)} \right) (\sup g'') \left(\sup \frac{\bar{F}}{f} \right) + g'(\bar{a}) \right] (v^{-1})' (\beta + g(\bar{a})) , \quad (69)$$

where α, β are given in equation (66), and $\bar{F}(x) = P(\eta \geq x)$. Using equation (68) yields:

$$|\mathcal{C}_A - \mathcal{C}_B| \leq \Lambda \mathbf{E} |A(\eta) - B(\eta)| ,$$

as required.

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